

A Si-photodiode radiometer based on artificial neural networks for daily instantaneous global horizontal solar radiation measurements

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Dissertation submitted in fulfilment of the requirements for the degree *Master of Science in Physics* at the North-West University

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Dedication

This research is dedicated to the memory of my mother, Mrs Tebogo P. Sebetlela., whose braveness, guidance and compassionate soul in this world has paved a good life for me.

Abstract

A low cost Si-photodiode based radiometer that uses a transimpedance amplifier was designed, developed and used to measure daily instantaneous global solar radiation on a horizontal platform. The design together with a reference CMP11 pyranometer were connected to a data logger and daily measurements recorded at 10 s intervals for a period spanning six months. The measurement period extended from June to November 2017. The photodiode suffered from nonlinearities and spectral mismatches but it was corrected using an artificial neural networks (ANNs). Daily voltage data measured over a period of six months recorded at Mafikeng were used to create, train and test ANN that uses the Levenberg-Marquardt (LM) algorithm, and the sigmoid as the activation function, with photodiode voltages as inputs and global solar radiation measured by the reference CMP11 as targets. Two separate ANNs for summer and winter were developed, validated and tested using the data recorded on clear days in both winter and summer. ANN estimated irradiances were further corrected via a method that involved the design of an average difference correction function for that period. Daily deviation functions based on the simple difference between ANN estimated and CMP11 measured irradiances were obtained. The average deviation function for each season was estimated using insolation obtained on clear days in that season and it was used to adjust radiation of that whole season. An average difference correction function (dcf) was then calculated for that season by simply negating the average deviation function. This average difference correction function for each season was saved on the computer and applied to correct all season ANN estimated irradiances. For winter, this function was found to resemble the negated second derivative of the sigmoid function. Radiometer performance analysis shows average

root-mean square errors (rmse) of the measured irradiance dropping from $\sim 16 \text{ W/m}^2$ to $\sim 9 \text{ W/m}^2$ in summer and from $\sim 27 \text{ W/m}^2$ to $\sim 7 \text{ W/m}^2$ in winter. This shows that a reliable, low cost radiometer was successfully designed that could be used for renewable energy projects currently running on the Mafikeng campus.

Overallly ANN and signal processing techniques have been successfully applied to develop a reliable radiometer that could be used for long term measurements in place of the expensive standard reference. The novelty of the radiometer and unique correction method designed shows that one can use any photodiode even if its spectral response does not match the reference. In addition, there may even be no need to worry about the exact horizontal setting of the photodiode. In most cases, empirical methods and models have been developed and used to calculate and predict global solar radiation for a particular location. This involves using data previously collected from meteorological stations. In such cases, only results concerning mismatches have been reported. This may be the first time where ANN estimated irradiances are themselves corrected to improve the accuracy of the ANN estimations.

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List of symbols and notation

B	Bandwidth
e	Residuals
E_g	Energy gap
G_sc	Solar constant
h	Planck's constant
HL_j	Output of Hidden Layer j
I	Current
k	Boltzmann constant
N	Number of measurements
r	Correlation coefficient
S	Sensitivity of the CMP11 pyranometer
Si	Silicon
t	Time
T	Absolute Temperature
t_i	Target (CMP11 measured) irradiance
w_{ij}	Weighting function
x_i	Input voltage
y_i	ANN estimated irradiance

Greek symbols

β	Sensor horizontal tilt angle
λ	Wavelength

Acronyms

ANN	Artificial Neural Network
CSIR	Council for Scientific and Industrial Research
DAS	Data Acquisition System
dc	Difference correction
dcf	Difference correction function
df	Deviation function
IEC	International Electrotechnical Commission
ISO	International Organization of Standards
eV	Electron volts
IEA	International Energy Agency
IR	Infrared
FOV	Field Of View
LM	Levenberg-Marquardt
mae	Mean Absolute Error
MLP	Multi-Layer Perceptron
NUV	Near Ultraviolet
PD	Photodiode
PIC	Peripheral Interface Controller
RAM	Random Access Memory
rmse	Root-Mean Square Error
UV	Ultraviolet
VIS	Visible

Chapter 1: Introduction and background

1.1 Introduction

The provision of secure, affordable and modern energy for all citizens is central to poverty reduction and economic growth. Economic and social development tend to go hand-in-hand with energy sector transformation. Access to modern energy is also vital for economic development at a household and community levels. Global energy consumption is predicted to grow by 53 % from 2008 to 2035, with the maximum rate of 83 % in developing countries [\[1\]](#). For some poor households, a large share of their income may be directed towards low quality and often expensive energy sources, such as kerosene and candles for lighting, mobile phone charging at retail stations and dry cell battery technology for electricity. These households also have limited options to meet their basic cooking needs, and typically rely heavily on fuels and technologies which are inefficient, polluting and time consuming to provide and use. According to a report by [IEA \[2\]](#), it is estimated that 18% of the global population (1.28 billion people) are still living without electricity. Furthermore, around 2.8 billion people, which is 38% of the global population, and almost 50% of the population in developing countries lack access to clean cooking. Most families cook their daily meals using solid biomass in traditional stoves. The report further goes on to mention that in 25 countries, mostly in sub-Saharan Africa, more

than 90% of households rely on wood, charcoal and waste for cooking. Collecting this fuel requires an excessive amount of hours each year, disproportionately affecting women and children who are usually assigned these chores. Burning fuels creates noxious fumes linked to 2.8 million premature deaths annually. Sub-Saharan Africa accounts for almost 14% of the worlds population, but only 4.5% of global primary energy demand. There has been, however, a positive trend in sub-Saharan Africa, where electrification efforts have exceeded population growth since 2014. Solid biomass makes up over half of total primary energy demand, mainly for household cooking. Coal and oil account for broadly equal shares and together meet a third of total primary energy demand. Coal demand is largely concentrated in South Africa for power generation, while oil demand of around 2 million barrels per day is more evenly distributed across the region. Figure 1.1 shows the average number of hours spent collecting fuel per day per household in sub-Saharan Africa. It also shows the percentage of the population that rely on biomass for cooking. A high reliance on biomass for cooking in many countries means that women and children without clean cooking access spend an average of 1.4 hours/day collecting fuel.

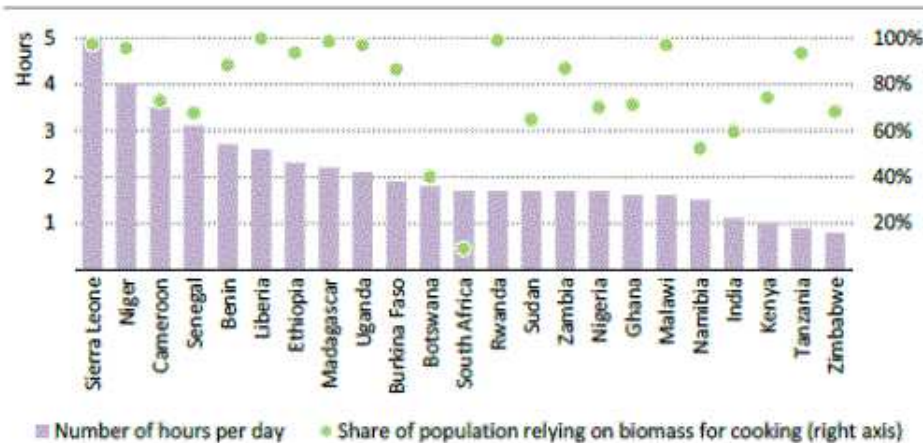


Fig. 1.1. Average number of hours spent collecting fuel per day per household in sub-Saharan Africa and India [2].

Renewable energy sources like wind power and solar power are excellent examples of development strategies that are sustainable. According to the United Nations, sustainability means development that meets the needs of the present without compromising the ability of future generations to meet their own needs. Solar energy embodies this widely accepted definition of sustainability because the sun's energy can be used indefinitely without diminishing its future availability. An essential part of developing sustainable communities is conservation of energy sources and the use of renewable and clean energy. Making use of solar power, geothermal heating and cooling systems, and wind energy can significantly reduce a community's reliance on gas, coal, and other forms of energy. Solar energy is a major renewable energy source with the potential to meet many of the challenges facing the world. It is a safe alternative which can replace current fossil fuels like coal and gas for generation of electricity that produce air, water, and land pollution. Use of solar energy will eliminate these unsafe and unclean consequences of using conventional fossil fuels.

Before solar radiation measurements can be made on the Earth's surface, it is important to first compare the variation in the solar radiation spectrum, from extraterrestrial level, to sea level. Figure 1.2 shows the solar radiation spectrum. Extraterrestrial solar radiation is external wavelengths received at the top of the Earth's atmosphere, which can range from ultraviolet to infrared emissions. The shaded areas indicate solar radiation wavelengths that are absorbed by the atmosphere. The spectral distribution of extraterrestrial solar radiation follows approximately the distribution of a blackbody at a temperature of 5762 K, whereas the solar radiation spectrum values at sea level are always lower than the extraterrestrial, due to absorption by the Earth's atmosphere. The changes in extraterrestrial solar radiation, atmospheric scattering (air, and dust) and atmospheric absorption (O_3 -ozone, H_2O -water vapour and CO_2 -carbon dioxide) cause solar radiation variability

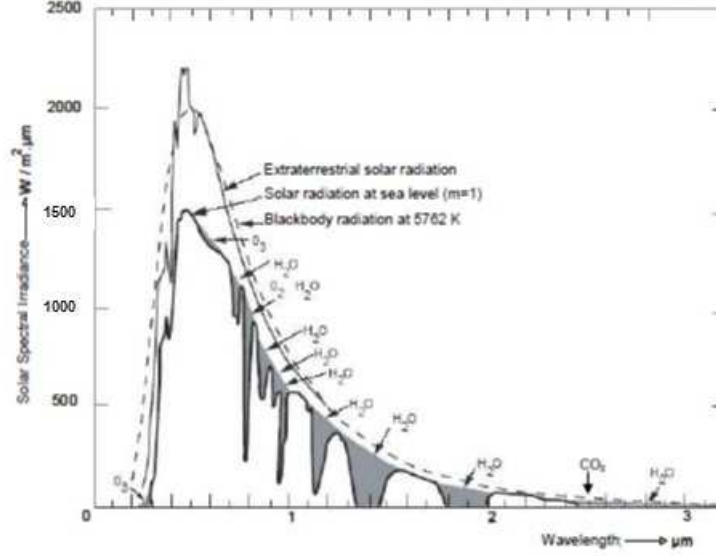


Fig. 1.2. The spectral distribution of extraterrestrial radiation and radiation at sea level, compared with black body radiation. [4]

on the Earth's surface. Clouds absorb very little solar radiation, which explains why they do not evaporate in sunlight. The effect of clouds on solar radiation is mainly scattering and reflection. Most of the solar radiation lies between 300 nm and 1200 nm wavelengths. It peaks around 450 nm, asymptotically decreasing to zero with higher wavelengths. Solar irradiance incident on a unit surface area, oriented normal to the sun's rays, outside the atmosphere of the Earth, at the mean sun-earth distance, is called the *solar constant*, G_{sc} . This quantity is measured from space through the use of satellite data and has a value of 1367 W/m^2 , which changes by approximately 0.01% over a period of 30 years [3]. Theoretically, radiation is emitted from the sun at all wavelengths, so that the integration of solar irradiance over all wavelengths is equal to the solar constant. However, 95% of the extraterrestrial radiation lies in the wavelength range 0.2 to $2.6 \mu\text{m}$ and 99 % in the range 0.217 to $10.94 \mu\text{m}$. Extraterrestrial solar radiation is available to every region on earth, but only a fraction of this radiation reaches the ground. This fraction may vary depending on the weather conditions and can be as high as 85% on a clear day to as low as 5% on a very cloudy day. Extraterrestrial solar irradiance also varies and its value G_{on}

on a plane normal to the radiation on the n_{th} day of the year, counted from January 1st, can be calculated [5] as :

$$G_{on} = G_{sc} \left[1 + 0.033 \cos \left(\frac{360n}{365} \right) \right] \quad (1.1)$$

The yearly variation of the extraterrestrial solar irradiance is shown in Fig. 1.3 where the red graph shows the solar constant. It is lowest around winter time of this region and highest around December-January.

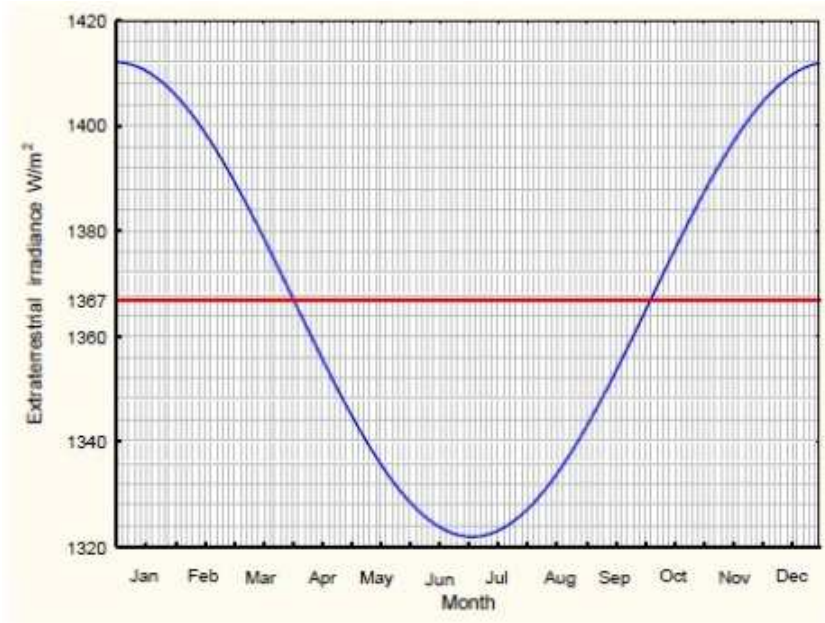


Fig. 1.3. Yearly variation of the extraterrestrial solar irradiance [6].

Figure 1.4 illustrates the amount of incoming solar radiation that is either absorbed or reflected as it traverses the atmosphere to Earth. It shows that 19% of the incident radiation is absorbed by clouds and the atmosphere, while a total of 30% is reflected by the atmosphere, clouds and the Earth. As a result only 51% of the incident radiation is absorbed by land and oceans.

Global solar radiation impinging on a horizontal surface is also referred to as global horizontal solar radiation. This radiation is made up of the direct and diffuse solar radiation components. Meteorological stations usually measure global and diffuse solar irradiance received on horizontal surfaces. Information about the availability of solar radiation on a horizontal surface is essential for the optimum design and study of solar energy systems. The data are needed by engineers, architects and scientists working with the design and testing of photovoltaic, thermal and other solar systems. The South African Weather Service is the main source of ground measurement irradiation data in South Africa. While global radiation on a horizontal plane is measured at numerous meteorological stations throughout South Africa, Mafikeng relies on the Vryburg station (100 km away) for such data. Solar radiation is responsible for many processes which occur on the earth's surface and its research finds applications in many science and engineering fields. Knowledge and estimation of solar radiation available at a specific location is of great importance for designing and performance evaluation of solar energy conversion systems [7], [8]. How-

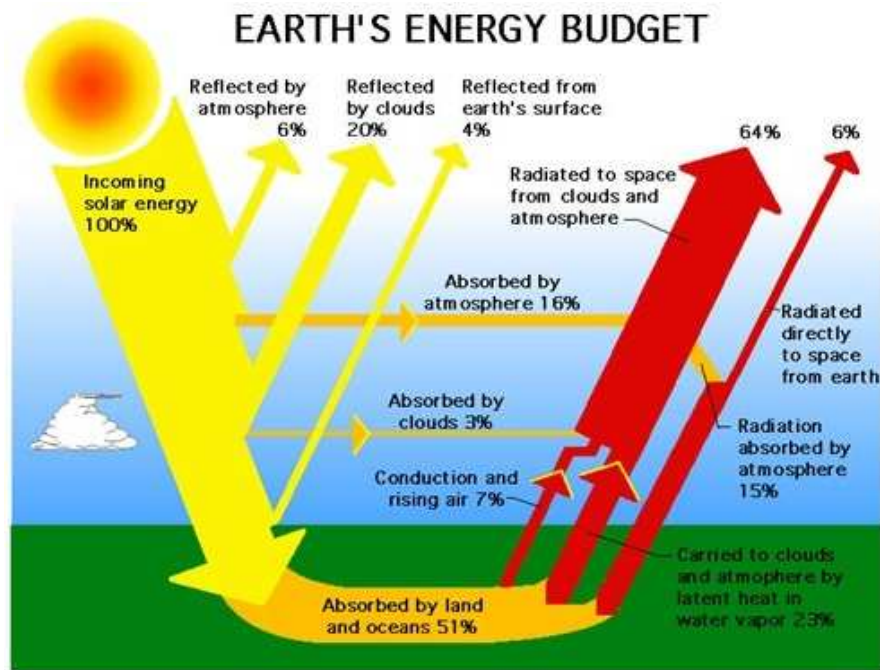


Fig. 1.4. An illustration of the Earth-Sun energy budget [3].

ever, in many geographical locations, global solar radiation is not measured because it is too expensive to purchase and maintain the apparatus and equipment required. Hence some researchers have employed empirical methods and models to calculate and predict global solar radiation for a particular location [7], [9], [10]. Wang et al., [11] reported that there has been a critical shortage of solar radiation data in many places around the world and this has prevented optimum use of the available solar energy resource. Ehsani et al., [12] pointed out that although data collected with the manual solar radiometers have proven to be reliable and advantageous, the process of data collection is tedious and time consuming. As such, the use of manual instrumentation is not effective under rapidly temporally varying atmospheric conditions. It also requires constant attention for operation.

South Africa is one of the countries in the world that receives a large amount of renewable energy resources, especially solar energy. Most areas receive a daily average of between 4.5 and 6.5 kWh/m^2 and a yearly average of more than 2500 hours of sunshine [13]. This amount of energy simply symbolizes that generating energy from renewable sources can be of low-cost for developing countries if technologies are implemented effectively. However, the unavailability of proper technologies hampers efforts to successfully harness the energy. Most parts of Southern Africa have abundant solar energy resources throughout the year, making this region appropriate for the implementation of small scale solar domestic applications such as solar heating and cooking [14]. Figure 1.5 shows the solar radiation map of South Africa. Solar radiation data presented was derived from satellite imagery. It shows that Mafikeng town receives its fair share of this natural resource averaging about 2400 kWh/m^2 of radiation per year. Although solar energy resource maps are available in South Africa, most are generated from satellite data that does not provide good quality. The scale is generally too large to provide reliable radiation data on

which to make technology and investment decisions [16]. Microclimate and topographical differences as well as changes in the location of a few hundred kilometres may result in a significant change in radiation parameters. Hence, the study of solar radiation using local climatic conditions is invaluable [17]. Therefore, there is a need to use alternative methods to estimate global solar radiation by using meteorological parameters of different geographical locations in the country.

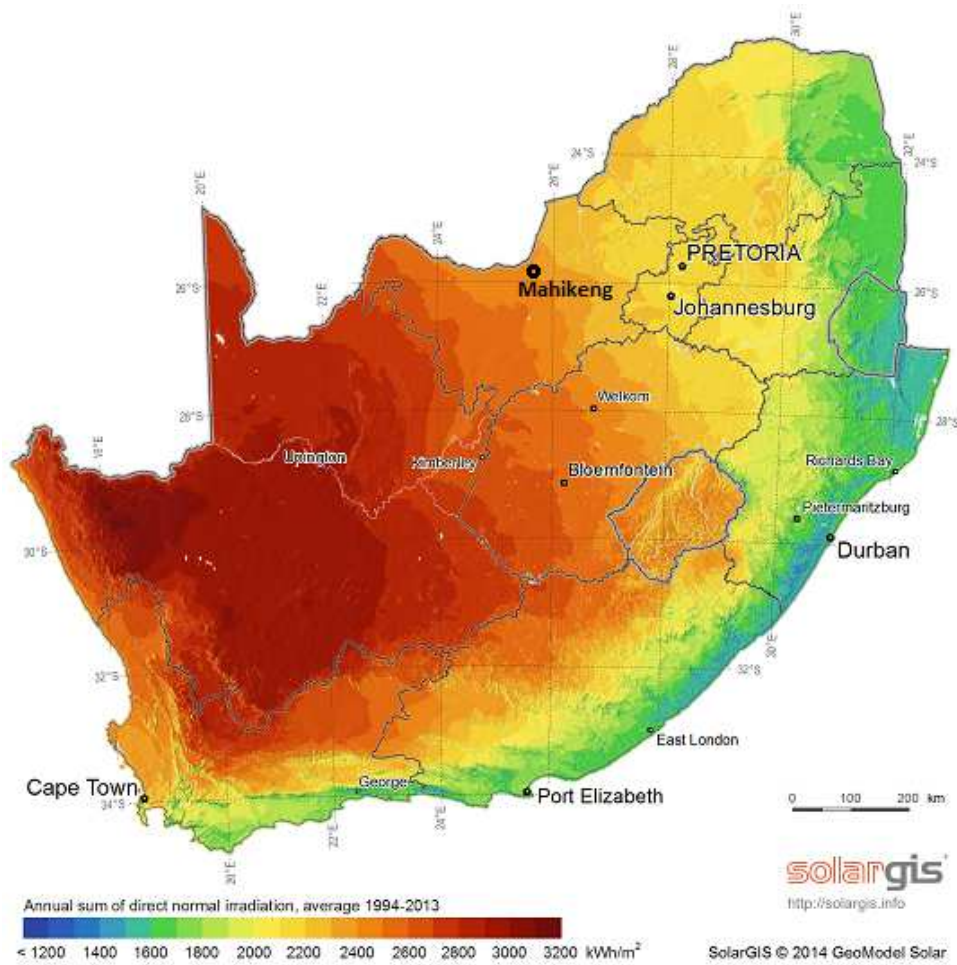


Fig. 1.5. Solar radiation map of South Africa. Mafikeng town is situated on latitude $25.86^{\circ}S$ and longitude $25.64^{\circ}E$ [18].

With an interest growing in the deployment of solar energy systems, the accuracy of irradiance measurements becomes increasingly important. Pyranometers are world class standard devices used to measure the amount of solar radiation impinging on a surface.

Solar radiation measurements are available for a number of locations, while high accuracy pyranometers are used in the bigger cities of South Africa. A number of these pyranometers however, appear to be calibrated less often than what manufacturers recommend [19]. Many environmental parameters affect the responsivity of the pyranometer such as relative humidity, temperature, and air mass. Studies are therefore warranted to better understand how these factors interact when they influence pyranometric and radiometric responsivities. Some general effects of these parameters are listed below :

- air mass : proportionately less transmittance of near ultra violet (NUV) and blue wavelengths as air mass increases;
- clouds : cloudy skies transmit proportionately more NUV and blue wavelengths than do clear skies;
- turbidity : complex scattering and absorption relationships;
- water vapour : sharp absorption peaks in selected wavelength bands (724, 824, 938, and 1120 nm);
- albedo : multiple reflection between the ground and clouds can be important for highly reflective surfaces; ground albedo is highly site and season dependent.

Just like all instruments, instruments for solar radiation measurements usually have measurement errors associated with them. These are attributed to sensitivity, response characteristics and other factors common to ordinary meteorological instruments. In addition to the above mentioned influences, the following properties also cause measurement errors common to these instruments :

- Wavelength characteristics - The absorption coefficient of the radiation sensor surface and the transmission coefficient of the glass cover or glass dome of a radiometer should be constant for all wavelengths of solar radiation. In reality, however, these coefficients

vary with wavelength. Since this wavelength characteristic differs slightly from radiometer to radiometer, observation errors occur when the energy distribution of solar radiation against wavelength varies with the sun's elevation or atmospheric conditions.

- Characteristics against elevation and azimuth - The output of an ideal pyranometer decreases with lower sun elevation angles in proportion to the cosine of the zenith angle. In reality, however, the output varies with the sun's elevation or azimuth due to the uneven absorption coefficient and the shape of the radiation sensor surface.
- Temperature characteristics - A thermopile is a non-linear device so the heat conductivity of a thermopile-based radiometer depends on temperature. This means that the sensitivity of these instruments vary and errors occur when the ambient temperature and the temperature of the radiometer change.
- Field of View - The field of view of pyranometers differ. If the field of view differs, the extent of influence from diffuse radiation also differs. Radiometers with different fields of view may make different observations depending on the turbidity of the atmosphere.

In addition to the above, dust coating over the sensor dome can shield part of the incoming solar radiation, causing an underestimate of measured irradiances. Shadows on the sensor can also lead to underestimates.

Presented below is a list of ISO/IEC radiometric standards used in the field solar radiation measurements [\[20\]](#) :

- ISO 9059:1990 : Solar energy - Calibration of field pyrhemometers by comparison to a reference pyrhemometer .
- ISO 9060:1990 : Solar energy - Calibration and specification of instruments for measuring hemispherical solar and direct solar radiation.
- ISO 9845-1:1992 : Solar energy - Reference solar spectral irradiance at the ground

at different receiving conditions.

- ISO 9846:1993 : Solar energy - Calibration of a pyranometer using a pyrliometer.
- ISO 9847 :1992 : Solar energy - Calibration of field pyranometers by comparisons to a reference pyranometer.
- ISO 9901:1990 : Solar energy - Field pyranometers - Recommended practice for use.

1.2 Problem statement

Mafikeng is located in the semi-desert north-west part of South Africa at a latitude of $25.86^{\circ}S$ and a longitude of $25.64^{\circ}E$ as indicated on the solar radiation map of South Africa presented in Fig 1.5. At the Mafikeng Campus of North-West University, there is an active research group working on renewable energy projects that involve the development and evaluation of solar receivers and solar thermal energy storage systems [14], [21]. There are a number of renewable energy projects currently running. The projects range from performance evaluation of different types of solar cookers, through photovoltaic to thermal energy storage systems. To effectively characterize performances of such systems and evaluate their efficiencies, incident solar radiation should be accurately measured and used as a base input. Accurate measurement of solar irradiance is necessary for the successful implementation of solar power systems, both photovoltaic and solar thermal [22]. The research group has a Kipp & Zonen CMP11 secondary standard pyranometer that is used as a reference, and it costs around US \$4000. However, for projects that run for extended periods of time, the expensive CMP11 cannot be deployed because of degradation that may occur. In some of the work done, there is need for continuous monitoring of solar radiation over an extended period of time. This justifies the need to design a low-cost

radiometer that could be deployed for such long periods.

Most villages in the North-West province of South Africa are not connected to the national grid and people depend on firewood for their daily energy requirements. To alleviate these problems, there are concerted efforts by the South African Department of Energy, rural electrification decision makers, and other stake holders to introduce renewable solar energy resources in such places. But before this can be done, there is need to assess the amount of this natural solar resource available in such places. The reference CMP11 pyranometer cannot be committed and deployed to such places. This calls for low cost solar radiometers and data loggers that can be left to run unattended collecting the vital information. It is therefore imperative to design and use a low-cost radiometer for these purposes.

1.3 Aims and objectives

The aim of the work reported here is to design, develop and characterize the performance of a Si-photodiode radiometer used to measure incident global horizontal solar radiation. Si-photodiodes are preferred for this application as the device will be used to assess long term performances and evaluate efficiencies of photovoltaic projects currently running on the Mafikeng campus. Low-cost experimental set-ups make it possible to do experiments in universities with limited resources, especially in developing countries. In addition, such low-cost solar radiation measurement systems may be used by undergraduate students and pupils in high schools around Mafikeng so as to motivate physics students to do research in renewable energy [\[21\]](#). This is one of the vital areas of research in most developing countries considering the energy crisis faced by many developing countries today.

The designed radiometer will be calibrated against the CMP11 reference using data gathered during a measurement period spanning six months. The Si-photodiode to be used

suffers from non-linearities and spectral mismatches, so artificial neural networks (ANNs) will be used to match the two devices. The purpose of linearization is to provide an output that varies linearly with some variable even if the sensor output does not. Results of the photodiode linearization technique based on ANN and the difference correction method will be compared in terms of achievable irradiance accuracy through consideration of the resultant linearity and root-mean square errors (rmse).

1.4 Outline of the dissertation

The dissertation consists of seven chapters. Chapter 1 presents a general introduction and background of what the research is about. In the same chapter, research problem statement and aim and objectives of the research have been conversed. Chapter 2 reviews previous work in literature related to the research proposed here. The chapter emphasizes on solar radiation measurements and application of ANNs to solar radiation estimation. Chapter 3 presents a theoretical framework that was used to guide the design of the proposed radiometer. Chapter 4 depicts instrumentation required to successfully accomplish the presented objectives. Chapter 5 presents the experimental characterization methodology and procedures used. This chapter deals with the development of the ANN models and the use of difference correction functions to match CMP11 measured irradiances and ANN estimated irradiances. Chapter 6 presents a discussion of the experimental results obtained. The chapter starts by showing the spectral mismatches between the two devices followed by the non-linear characteristics of the photodiode. Daily measured voltages are then presented for summer and winter periods. This was followed by ANN estimated irradiances and in comparison to the CMP11 measured. The chapter concludes by presenting radiometer performance ratings before and after difference correction of ANN estimated

irradiances for both seasons. Chapter 7 concludes this research work. It abstracts the novelty of the designed radiometer and finally, recommendations for future work are suggested.

Chapter 2: Literature review

2.1 Introduction

This chapter presents a review of literature supporting the research. The chapter dwells on articles reported in literature regarding solar radiation measurements and application of ANNs to solar radiation estimation.

2.2 Solar radiation measurements

[Ehsani et al., \[12\]](#) presented instrument design features as well as some performance and experimental results for the automated solar radiometer. The automated radiometer has 10 separate silicon-photodiode based channels that allow near-simultaneous solar spectral measurements through narrow bandpass filters from the visible to near-IR regions. The Si-photodiode detectors were temperature stabilized using a heating temperature controller circuit to ensure uniform responsivity of the detectors throughout the course of data collection. The instrument was mounted on a tracker that actively tracked the sun with a $\pm 0.05^\circ$ tracking accuracy. A data acquisition system (DAS) controlled all the activities of the solar radiometer system and it was initialized by a menu-driven program. The digitized data were stored in a 32-kbyte nonvolatile random access memory (RAM), which was

sufficient to store approximately 1300 complete 10-channel datasets. With a one minute sample rate, the instrument could continuously collect data for about 22 hrs. At the end of a data collection period, the DAS could be hooked up to a personal computer to transfer the collected data into the computer via the serial port. [Patil \[22\]](#) reported on the design and development of a PIC microcontroller-driven photodiode based pyranometer for measuring solar irradiance in the visible spectral range (approx. 400 to 750 nm). The designed radiometer communicated with a personal computer a weather station enabling it to be used for remote sensing and data logging applications. They recommend the design especially in those applications where cost may be a deciding factor. However, they do not give an indication of how well the design performs when compared against standard instruments used in the field.

[Mukaro et al., \[23\]](#) demonstrated the operation of a low-cost silicon-based pyranometer in combination with a self-designed low-power microcontroller-based data acquisition system (SIMBADAS) for measuring global horizontal solar radiation. The SIMBADAS performance was evaluated on the basis of experimental instantaneous global horizontal solar radiation data obtained between January and October 1997. The SIMBADAS was initially calibrated against the Eppley PSP, and the resultant calibration equation relating the SIMBADAS output to the Eppley PSP was :

$$G_H = 6.40D + 0.0034D^2 \quad (2.1)$$

where G_H is the calculated global solar radiation and D is the data value recorded by the SIMBADAS. Experimental field tests and comparisons with the Eppley pyranometer indicated that the accuracy of the SIMBADAS was fairly good, typically $\pm 13W/m^2$ except during partly cloudy days.

[Macome et al., \[24\]](#) presented a low-cost direct solar radiation detector (DSRD) designed

using a silicon diode as a detector for direct solar radiation. The detector was characterized with respect to the spectral response, polar response and environmental stability. Experimental results revealed that the DSRD followed the Eppley normal incidence pyrheliometer very closely and could therefore be used instead. Results also indicated that the correlation between the DSRD and the NIP data was good with a correlation factor close to unity and a root mean square value close to zero.

In another application, [Federer et al., \[25\]](#) developed a simple integration pyranometer for measuring daily solar radiation using a small, accurate and inexpensive instrument to integrate daily solar radiation flux density. Two silicon solar cells and a Curtis integrator were employed in the study. The results indicated that the response was linear, temperature sensitivity was low and not much inaccuracy was caused by the cosine response except at high latitudes. [Miguel et al., \[26\]](#) presented the design, construction and characterization of a new photodiode based pyranometer as a new and inexpensive pyranometer for the visible spectrum range (~ 400 to 700 nm), whose principal characteristics were accuracy, ease of connection, immunity to noise, remote programming and operation, interior temperature regulation and cosine error minimization. The designed device costs ten times lower than that of commercial thermopile-based devices. The experimental tests carried out on the device showed similar characteristics to those of thermopile based pyranometers. Results also indicated that the newly developed pyranometer could be used in any installation where reliable measurement of solar irradiance was necessary, especially if cost became a deciding factor when choosing a pyranometer. [Shafa et al., \[27\]](#) demonstrated low cost pyranometer designs for measuring solar irradiation using copper (Cu), iron (Fe), and aluminium (Al) metallic slabs. The designed pyranometers were calibrated against Standard Pyranometer Apogee (Model SP-110 and Model SP-230) that both have spectral responses ranging from 300 nm to 2800 nm. The experimental results indicated

that Al-fabricated pyranometer response was 1000 W/m^2 after 100 minutes, while the Fe-fabricated reached 800 W/m^2 at 250 minutes, and the Cu-fabricated pyranometer gave 800 W/m^2 at 180 minutes. Results also indicated that the matching improvement between the designed pyranometers and standard pyranometer was 98%.

[Michalsky et al., \[28\]](#) presented an improved Si-photodiode-based rotating shadow-band pyranometer suited for radiometric observations by applying empirical derived corrections for measuring total horizontal, diffuse horizontal, and direct normal irradiance to simulate thermopile sensors. Results indicated that the daily integrated values after corrections had been applied, for total horizontal, diffuse horizontal, and direct normal irradiance measured with rotating shadow-band radiometer, reached an average agreement of better than 1%, 3% and 2.5% respectively, compared to thermopile results. Results also indicated that 10 minutes absolute integrated values hardly diverged by more than 20 W/m^2 from the thermopile values. [Bilguun et al., \[29\]](#) developed a simple photovoltaic band spectral pyranometer and quantum meter for measuring a spectrally divided amount of solar irradiance and photon flux density using photovoltaic cells and optical filters. A solar simulator was first used to calibrate both instruments, before field evaluation. Performance of the developed pyranometer was evaluated in three various weather conditions, namely clear, partly cloudy and cloudy skies. Field results revealed that the response time of the developed device was four seconds faster compared with the response time of the commercial pyranometer. Results also indicated that the integrated outputs of both the developed pyranometer and the commercial spectro-radiometer were well related.

2.3 Artificial neural networks for solar radiation estimation

Many previous researchers estimated global solar radiation by using artificial neural networks (ANNs). [Crisosto et al. \[15\]](#), presented a method to predict the global horizontal irradiance (GHI) one hour ahead in one-minute resolution using Artificial Neural Networks (ANNs). A feed-forward neural network with LevenbergMarquardt Backpropagation (LM-BP) was used and was trained with four years of data from all-sky images and measured global irradiance as input. The pictures were recorded by a hemispheric sky imager at the Institute of Meteorology and Climatology (IMuK) of the Leibniz Universitt Hannover, Hannover, Germany (52.23° N, 09.42° E, and 50 m above sea level). The time series of the global horizontal irradiance was measured using a thermopile pyranometer at the same site. This new method was validated with a test dataset from the same source. Results indicated that calibration agreement between predicted and observed irradiance were reasonable for the first 10-30 min. Results also indicated that both the root mean square error (rmse) and the mean absolute error (mae) were reduced over one-hour prediction by approximately 40% compared to the reference persistence model under various weather conditions, which demonstrated the high capability of the algorithm, especially within the first minutes.

[Chiteka & Enweremadu \[16\]](#) presented work on predicting global horizontal solar irradiance in Zimbabwe using artificial neural networks. The estimation used geographical data of altitude, latitude and longitude and meteorological data of humidity, pressure, clearness index and average temperature as inputs to an ANN model. They used a neural network with an input layer that has seven inputs and one hidden layer and an output layer with one output. For all the models evaluated, they found that a network with

10 neurons and a tansig transfer function in both the input and output layers was the best predictive model. The developed network achieved a coefficient of determination of 99.89%, a root mean square error of $0.223 \text{ kWh}/(\text{m}^2/\text{day})$, a mean absolute error of $0.17 \text{ kWh}/(\text{m}^2/\text{day})$ and a mean absolute percentage error of 2.56%. Further statistical analyses revealed that clearness index, temperature and humidity had significant contributions of 19%, 18% and 17%, respectively, to the ANN estimated irradiances. [Mohandes et al., \[30\]](#) used latitude, longitude, altitude and sunshine duration as weather input data from 41 weather stations to an ANN to predict global horizontal solar radiation in Saudi Arabia. Data from 31 stations were used in training the ANN and the remaining data were used for testing.

[Notton et al., \[31\], \[32\]](#) applied ANNs to calculate the solar global irradiation on a tilted plane from global horizontal irradiation successively for hourly and 10-min time step data. Five years solar data accumulated in the Mediterranean site of Ajaccio, France was employed to develop and optimize the ANN. Results indicated that root-mean square error (rmse) precision for hourly data and 10-min data was 6% and 9% respectively. It was also observed that the root-mean absolute error (rmae) precision was 3.5% and 5.5 % respectively. In another application, [Notton et al., \[33\]](#) used ANNs to calculate global solar irradiance on tilted planes from horizontal global radiation only, using 10-minute time steps. The ANN was developed and optimized using five years of solar data and the accuracy of the optimal configuration was around 9% for the rmse and around 5.5% for the rmae i.e., similar or slightly lower than the errors obtained with empirical correlations available in the literature and used for the estimation of hourly data. [Lam et al., \[34\]](#) used ANNs to develop predication models for daily global solar radiation using measured sunshine duration for 40 cities covering 9 major thermal climatic zones and sub-zones in China. [Alam et al., \[35\]](#) used ANNs to estimate monthly mean hourly

and daily diffuse solar radiation based on weather data from 10 Indian stations which have different climatic conditions. [Alawi & Hinai, \[36\]](#) applied ANNs to predict solar radiation in areas not covered by direct measurement instrumentation. Input data that were used for building the network were : the location, month, mean pressure, mean temperature, mean vapor pressure, mean relative humidity, mean wind speed and mean duration of sunshine. [Tasadduq et al., \[37\]](#) used neural networks for the estimation of mean hourly values of ambient temperatures, a day in advance. Full year hourly values of ambient temperature were used to train a neural network model for the coastal location of Jeddah in Saudi Arabia. [Elminir et al., \[38\]](#) applied ANN modeling techniques to predict solar radiation data in different spectrum bands from meteorological data for Helwan (Egypt).

Using different combinations of day of the year, time day of year, air temperature and relative humidity, [Rehman & Mohandes, \[39\]](#) developed ANN-based model for the estimation of global solar radiation for Abha city in Saudi Arabia. [Mubiru \[40\]](#) estimated monthly average daily total solar irradiation on a horizontal surface for locations in Uganda by using an ANN technique, where both geographical and meteorological data were used to develop the model. [Benghanem et al., \[41\]](#) developed six ANN models for estimating daily global solar radiation in Al-Madinah (Saudi Arabia); based on different combinations of 4 inputs variables, namely : temperature, relative humidity, sunshine duration, and day of the year. It was found that the model using sunshine duration and air temperature as inputs, gave good accurate results with correlation coefficients of around 97.65 %. It was also noted that the developed ANN models gave better results than empirical models. [Premalatha & Arasu \[42\]](#) developed ANN models to predict the monthly average global solar radiation in India. They used nine input parameters, namely : latitude, longitude, altitude, year, month, mean ambient air temperature, mean station level pressure, mean

wind speed and mean relative humidity and only one output parameter which was the monthly average global solar radiation. Two different ANNs, each with four backpropagation algorithms, namely : gradient descent, Levenberg-Marquardt, scaled conjugate gradient and resilient back propagation algorithm were trained and tested. Meteorological data from five stations covering the geography of India were collected for a period of 10 years for training and testing the network. In this work, the Levenberg-Marquardt back propagation algorithm was found to be the best algorithm for training and testing of ANN models. [Prakash & Kumar \[43\]](#) also found the Levenberg-Marquardt back propagation algorithm as the best training algorithm in their work on the application of ANNs for predicting masses of unrefined sugar, during drying inside a natural convection greenhouse dryer.

While many reports in literature report on ANN models developed for predicting global radiation using many input meteorological variables such as number of sunshine hours, wind speed, clearness index, temperature, humidity, among others, (e.g., [\[16\]](#)), this work reports on application of ANNs to predict daily irradiances based on daily photodiode measured voltages. A neural network with an input layer that has just one input input was used together with ten hidden layers and an output layer with one output variable. In most of the reports, researchers used weather data measured previously and provided by weather stations scattered around these places (e.g., [\[16\]](#), [\[30\]](#), [\[35\]](#), [\[39\]](#), [\[42\]](#), [\[31\]](#), [\[32\]](#), [\[3\]](#) and [\[44\]](#)) . In the work reported here, a multi-layer feed forward neural network learning method is used to develop optimal neural networks for predicting the daily solar irradiation on horizontal surface from Si-photodiode measured voltages. In addition, correction procedures applied to ANN estimated irradiances are presented that show much better correlations.

Chapter 3: Theory

3.1 Introduction

This chapter covers a framework of the theoretical overview by illustrating the theoretical concepts associated with semiconductor devices. It also presents the architecture of the artificial neural networks employed in this study.

3.2 Semiconductor theory

Si-photodiodes are semiconductor devices that respond to high energy particles and photons. They operate by absorbing these to generate current that flows in the external circuit. This current is proportional to the incident radiation. The light is absorbed exponentially with distance and is proportional to the absorption coefficient of the device.. These diodes have found use in diverse applications that include spectroscopy, photography, analytical instrumentation, optical position sensors, surface characterization, laser range finders optical communications and medical imaging instrumentation among others.

When the energy of absorbed photons is lower than the band gap energy E_g , the photovoltaic effect does not occur. The limiting wavelength λ can be expressed in terms of E_g

as follows :

$$\lambda = \frac{hc}{E_g} = \frac{1240}{E_g} \quad [nm] \quad (3.1)$$

where $h = 6.626 \times 10^{-34}$ Js is Planck's constant and c is the speed of light. At room temperatures, E_g is ~ 1.12 eV for silicon so the limiting wavelength is 1100 nm.

Photodiodes can be operated with or without an applied reverse bias depending on the application. These are referred to as the photoconductive (biased) and photovoltaic (unbiased) modes. The photovoltaic mode is preferable because of the following properties - zero bias required, no dark current produced, linear operation, low Johnson noise, and high precision. In this mode the photodiode generates its own current similar to the way a solar cell does. On the other hand, the biased photoconductive mode has the following disadvantages - dark current is produced, high Johnson and shot noise, non-linear operation, and the need for an extra bias supply. Dark current is the current through the diode in the absence of light. It includes photocurrent generated by background radiation and saturation currents of the semiconductor junction. Johnson noise or thermal noise is caused by the random motion of carriers in a conductor. The dark current is the small current which flows when reverse voltage is applied to a photodiode under dark conditions. It is a source of noise for applications in which a reverse bias is applied to photodiodes.

The Si-photodiode can be represented by a current source in parallel with an ideal diode as shown in Fig 3.1. The current source represents the current generated by the incident radiation and the ideal diode represented by the p-n junction. In addition a junction capacitance C_j and a shunt resistance R_{sh} are in parallel with the other components. Series resistance R_s is connected in series with all other components in this model. R_L is the load over which the output voltage V_o is developed. where,

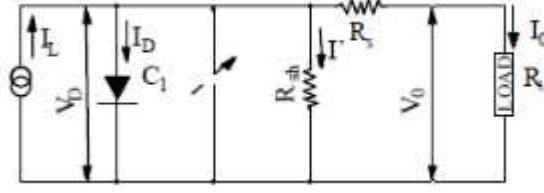


Fig. 3.1. Equivalent one diode solar cell model for the Si-photodiode [20].

I_L is the current generated by the incident light (proportional to the amount of light),

I_D is the diode current,

I' is the shunt resistance current,

V_D is the voltage across the diode,

I_o is the output current,

V_o is the output voltage.

Using the equivalent circuit in Fig 3.1 and solving for the output current, gives :

$$I_o = I_L - I_D - I' = I_L - I_s \left(\exp \frac{eV_D}{kT} - 1 \right) \quad (3.2)$$

where

I_s : photodiode reverse saturation current

e : electron charge

k : Boltzmann's constant

T : absolute temperature of the photodiode

The open circuit voltage V_{op} is the output voltage when I_o equals 0. Therefore, we have:

$$V_{op} = \frac{kT}{e} \ln \left(\frac{I_L - I'}{I_s} + 1 \right) \quad (3.3)$$

V_{op} varies logarithmically with respect to a change of amount of light and is greatly affected by variations in temperature, making it unsuitable for light intensity measurements.

The short-circuit I_{sh} is the output current when the load resistance R_L equals 0 and V_o

equals 0, yielding: Using the above equivalent circuit and solving for the output current, gives :

$$I_o = I_L - I_s \left(\exp \frac{e I_{sh} R_s}{kT} - 1 \right) - \frac{I_{sh} R_s}{R_{sh}} \quad (3.4)$$

3.3 Noise characteristics

Like other types of light sensors, the lower limits of light detection for photodiodes are determined by the noise characteristics of the device [20]. The bias current caused by the bias mode also causes shot noise defined as :

$$i_s = \sqrt{2qi} \quad (3.5)$$

where q is the electronic charge $= 1.602 \times 10^{-19}$, i is the bias current and i_s is the noise current. In most circuits the dominant noise is the thermal or Johnson noise of the feedback resistor defined as :

$$i_{jn} = \sqrt{\frac{4kTB}{R_{sh}}} \quad (3.6)$$

where k is the Boltzmann constant, B is the noise bandwidth, T is the absolute temperature, and R_{sh} is the shunt resistor.

The photodiode noise i_n is the sum of the thermal noise (or Johnson noise) i_{jn} caused by the shunt resistance R_{sh} and the shot noise is resulting from the dark current and the photocurrent.

$$i_n = \sqrt{i_{jn}^2 + i_s^2} \quad (3.7)$$

When a photodiode is used in an operational amplifier circuit, the dark current may be ignored since the applied voltage is the operational amplifiers input offset voltage only.

So photodiode noise can be expressed as :

$$i_n = i_j = \sqrt{\frac{4kTB}{R_{sh}}} \quad (3.8)$$

3.4 ANN theory

Multilayer perceptron neural networks (MLP) training algorithms are implemented for this analysis, which are the Levenberg-Marquardt. The Levenberg-Marquardt nonlinear least squares fitting method was used to model the BP21 voltages into estimated irradiances. A Multilayer Perceptron (MLP) network is the most common type of feed forward artificial neural network. Figure 3.2 shows the architecture of the ANN used in this application, which is a fully connected feed-forward neural network. It consists of three types of layers: an input layer, hidden layer and an output layer. The input, hidden and output layer are expressed in the indices of neurons i , j and k respectively. Neurons in input layer only act as buffers for distributing the input signals $x_i (i = 1, 2, \dots, N)$ to neurons in the hidden layer. While the input layer has 4321 voltage inputs and the output layer has the same number of irradiance outputs for summer, for winter the ANN has 3786 voltage inputs and 3786 irradiance outputs.

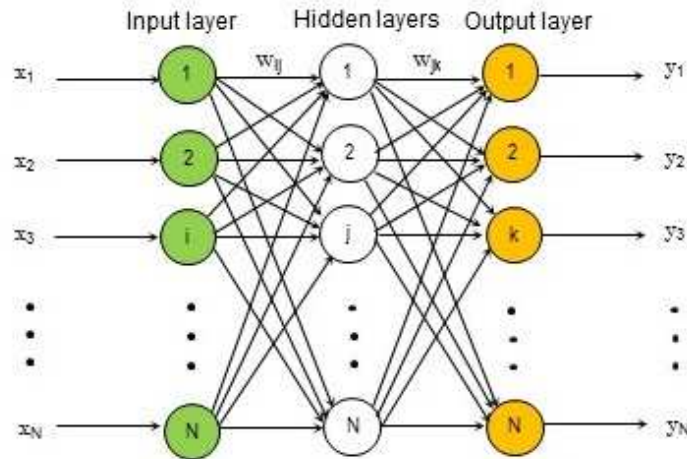


Fig. 3.2. Architecture of a feed-forward neural network used in this application.

Each neuron j in the hidden layer sums up its input signals x_i after weighting them with the strengths of the respective connections w_{ij} from the input layer and computes its

output HL_j as a function f of the sum. To generate the output signal, the value of x_i must be activated with the activation function. The sum of all weighted inputs is used by an activation function f to produce the output of the hidden layer and feed it forward to the output layer.

$$HL_j = f\left(\sum_{i=1}^N w_{ij}x_i\right) \quad (3.9)$$

where N is the number of neurons, and f is a non-linear activation function. The logistic sigmoid also known as the binary sigmoid was employed as the activation function in this study. This logistic sigmoid activation function is effectively employed in hidden layer neurons (processing unit) for squashing the output to certain values, which can be processed [45]. The backpropagation algorithm, a gradient descent algorithm, is the most commonly adopted MLP training algorithm. It gives the change Δw_{ij} in the weight of a connection between neurons i and j as follows :

$$\Delta w_{ij} = \eta \delta_j x_i \quad (3.10)$$

where η is a parameter called the learning rate and δ_j is a factor depending on whether neuron j is an input neuron or a hidden neuron.

Each hidden neuron j receives the output of each input neuron i from the input layer multiplied by a weight of w_{ij} . The output of neurons in the output layer, y_k is computed similarly from the hidden layer output as :

$$y_k = \sum_{j=1}^N (w_{jk} HL_j) \quad (3.11)$$

The error signal is propagated from the output layer to the hidden layer for the i^{th} iteration. Levenberg Marquardt (LM) algorithm is a popular method to solve nonlinear problems effectively due to its ability to converge from a wide range of initial input values. Its efficacy is due to the computation of Jacobian matrix [46]. The LM algorithm

is basically a Hessian-based algorithm for nonlinear least square optimization. For neural network training the objective function is the sum square error function of the type :

$$e = \frac{1}{2} \sum_{i=1}^N (t_i - y_i)^2 \quad (3.12)$$

where t_i is the target (or CMP11 measured) irradiance measured at time i and y_i is the corresponding network estimated irradiance. Once the input is supplied, the process calculating the output, computing the error function and updating the weights continued until the error function reached a pre-specified value or the weights no longer changed. At this point the training process stopped, then testing and operation of the new network was pursued [47], [48].

3.5 Spectral response theory

Responsivity of a radiometric sensor is the ratio of the detector output to the incoming radiation. It is expressed as :

$$S = \frac{S_{PD}}{E_\lambda} \quad (3.13)$$

where S_{PD} is the detector output signal, and E_λ is the amount of incident solar radiation.

For the CMP11 pyranometer used $S = 9.38 \mu V/(W/m^2)$. The variation of the detector output with wavelength is described by the spectral responsivity SR_λ expressed as :

$$SR_\lambda = \frac{dY_\lambda}{dX_\lambda} \quad (3.14)$$

where, $dY(\lambda)$ is the fractional change in the output due to a change $dX(\lambda)$ in the input at wavelength λ . The response of a photo detector to some incident radiation can be expressed as :

$$S_{PD} = \int E_\lambda SR_\lambda d\lambda \quad (3.15)$$

where S_{PD} is the photodiode output signal, SR_λ is the spectral response of the photodiode, and E_λ is the incident solar radiation.

Chapter 4: Instrumentation

4.1 The design

The instrumentation required to successfully calibrate the designed radiometer against the reference, and to use it to measure incident solar radiation throughout the entire day is presented in this chapter. Figure 4.1 shows the block diagram of the proposed measurement system. Incident solar radiation on the photodiode generates a voltage signal that will be amplified to give V_{PD} . Both instruments were mounted on the roof top of the renewable energy research group laboratory at North-West University, Mafikeng Campus. The photodiode voltage and the corresponding CMP11 voltage were measured by an Agilent 34970A data acquisition system (DAS) and recorded on a dedicated computer. Unlike the CMP11 pyranometer that uses active thermopile sensors, the proposed radiometer amplifier requires a power supply for successful photocurrent to voltage conversion. The solar radiometer instrument can be powered by a 12-V direct current power supply or a 12-V battery. The computer will be used to store the voltage signals and later process and display the corresponding irradiances. The solar radiometer instrument is automated in the sense that it requires no supervision throughout a data collection sequence under normal atmospheric conditions. The collected data can be retrieved through serial communication between the DAS and a personal computer via the RS-232 port. A

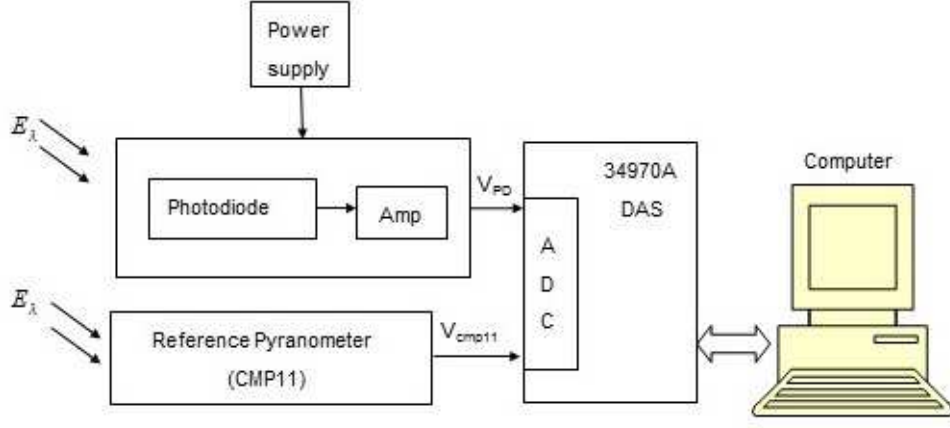


Fig. 4.1. Block diagram of the proposed solar radiation measurement system.

program for data retrieval must be run from the personal computer. The computer program sends a command to the DAS requesting the number of valid data points stored in the RAM. The program will then receive data from the DAS accordingly. Once the data retrieval process is completed, a completion message appears on the DASs display panel.

Figure 4.2 shows the circuit diagram for the developed solar radiation detector which consists of a photodiode connected in the photovoltaic mode of operation. Upon receiving incident solar radiation, the circuit converts the photo generated diode current into a voltage. Incident radiation creates charge carriers in the photodiode resulting in current I_D which is converted by the transimpedance amplifier into a voltage. The current generated in the photodetector is converted to a voltage by a transimpedance amplifier configuration. In a transimpedance configuration, the output voltage of the amplifier is equal to the output current of the detector multiplied by the feedback resistor used with the amplifier. The voltage developed across the feedback resistor was then recorded by the 34970A DAS together with the corresponding CMP11 voltage measured at the same time. The feedback resistor was selected not to exceed the dynamic range of the DAS (maximum of 4.5 V), but the choice is not critical as long as the value used does not result in

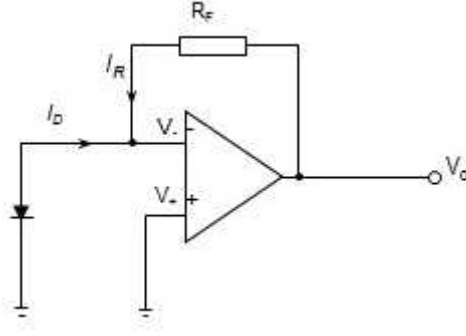


Fig. 4.2. Photodiode in unbiased or photovoltaic mode used to drive a transimpedance amplifier for solar radiation measurements.

saturation. A photodiode can be operated in one of the following two modes, namely : the photoconductive or the photovoltaic modes. In the photovoltaic mode, the photodiode is unbiased, while for the photoconductive mode, an external reverse bias is applied. The use of the photodiode in the photovoltaic mode increases the sensitivity of the photodiode. In this application, an unbiased photodiode is connected to a transimpedance amplifier which is used to convert the photodiode current to a voltage. Photocurrent flows in the reverse direction. In this unbiased mode, the feedback resistor R_F converts the very small photodiode current I_D to a voltage V_o , expressed as :

$$V_o = I_D R_F \quad (4.1)$$

A proper choice of the feedback resistor R_F is required for the design. Using too high a value will result in saturation of the radiometer. A feedback resistor set at $R_F = 7.0 \text{ k}\Omega$ was used to convert the solar generated photocurrent to a voltage.

4.2 Reference CMP11 pyranometer

Thermopile radiometers transfer the radiant energy falling onto a detector into heat energy and are generally considered spectrally non selective. The Kipp & Zonen secondary standard pyranometer with a sensitivity of $9.38 \text{ }\mu\text{V}/(\text{W}/\text{m}^2)$ was used as the reference

pyranometer in this application. It costs US\$4 000 which is way above reach of most higher learning institutions in the developing world. Although the CMP11 is a secondary standard, it has in-built temperature compensating circuits and this makes it more expensive than the Eppley PSP. The cost of these instruments is clearly out of reach of many research laboratories working on solar energy projects in the developing world and as such it is not economic to deploy them in the field. Figure 4.3 shows a picture of the CMP11 pyranometer on the left, while components that make up this pyranometer are shown on the right. The pyranometer consists of a fixed foot, a bubble level sensor and two adjustable feet for horizontal level setting. Among other features it has a connector cable for connecting the device to a data logger.

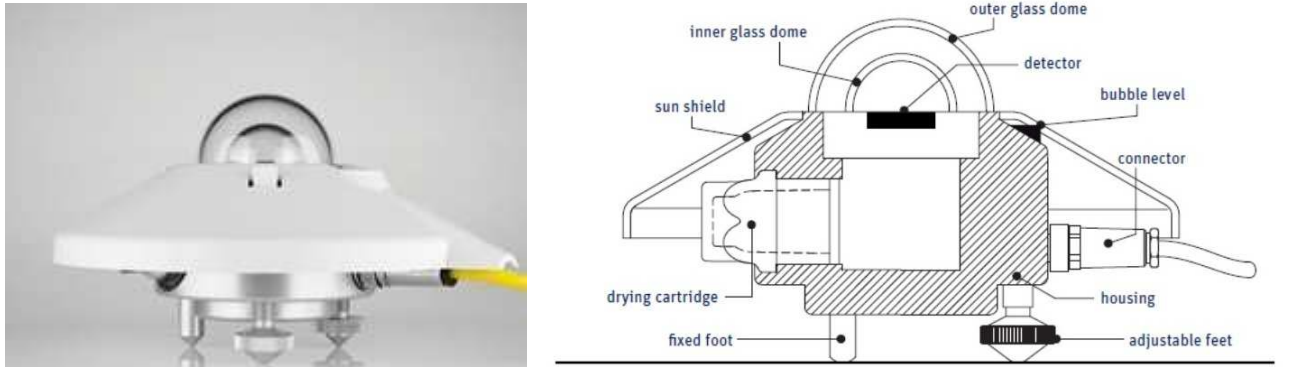


Fig. 4.3. Secondary standard CMP11 pyranometer (a) left - picture (b) right -components [49].

The manufacturer Kipp & Zonen [49] lists the specifications of the CMP11 secondary standard pyranometer as follows :

- Spectral response : 285 - 2800 nm
- Sensitivity : 7 - 14 $\mu V/(W/m^2)$
- Response time : < 5 s
- Directional response (up to 80° with $1000 W/m^2$: < $10 W/m^2$
- Temperature dependence of sensitivity ($-10^\circ C$ - $+40^\circ C$) : < 1 %

- Operational temperature range : $-40\text{ }^{\circ}\text{C} - +80\text{ }^{\circ}\text{C}$
- Maximum solar irradiance : 4000 W/m^2
- Field of view : 180°

While the silicon radiometer proposed has no temperature compensation mechanism, the CMP11 thermopile-based reference pyranometer used in this study incorporates compensation circuitry to overcome changes in instrument output with temperature.

4.3 Agilent 34970A data acquisition system

A commercial Agilent 34970A data logger is a multichannel data logger that was used to measure the two voltages. It has a 22-bit resolution and has up to 120 single-ended measurement inputs and scan rates of up to 250 channels per second (ch/s). Its internal memory of 32 K random access memory (RAM) can store data for a limited duration. When used as a data logger, the instrument will automatically stop collecting data when it reaches its maximum 32 K memory space. Because of its limited memory capacity, the device was used as a data acquisition system (DAS) which was connected to a dedicated computer that stored the measurements. The DAS was used to convert the analogue voltages into digital signals. Once the measurement process commenced, an excel file was opened on the computer where 10 s measurements were recorded. As the frequency at which measurements are taken is high, this file remains open until it is manually saved. Unfortunately if there are power interruptions, the entire file containing the measurements will be lost since it has not been saved. This happened a couple of times, during the summer season when heavy rains and thunderstorms disrupted the power. This means measurements for some days in the six month study period were therefore inevitably lost. The data collection mode may be interrupted at any time without loss of any

previously collected data. This feature allows the operator to stop the data collection routine. Figure 4.4 (a) shows a picture of the front panel of the data logger used. It is configured with a 20-channel relay multiplexer, making it a powerful, low-cost data logger for simple characterization applications, that are quick to set up and easy to run. It also has a flexible, modular design that makes it scalable from 20 to 120 channels, letting the user add actuators, digital input/output and analog output channels for simple control. Figure 4.4 (b) shows a screen shot from the computer showing a typical recorded data file.

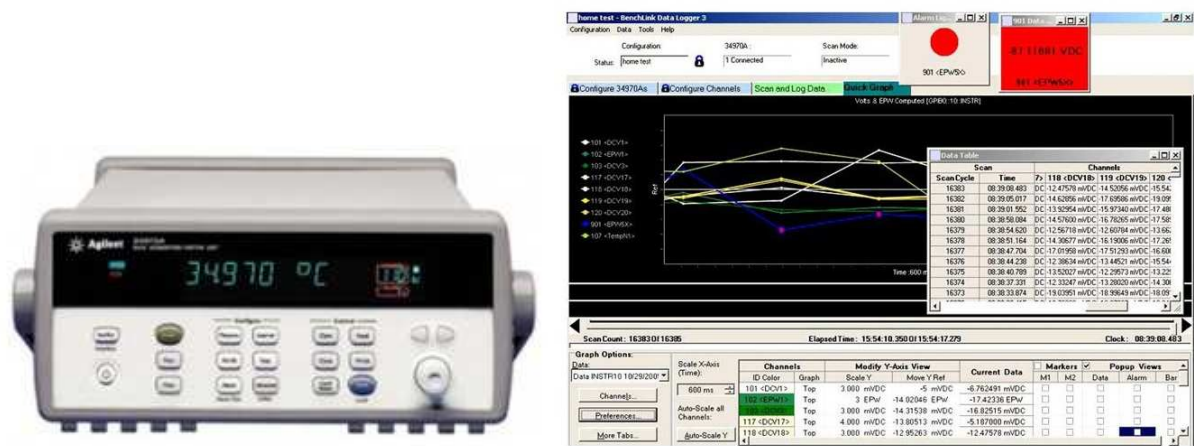


Fig. 4.4. (a) Left - Picture of the 34970A data logger front panel, (b) right - screen shot from the computer showing a typical recorded data file.

Chapter 5: Methodology and procedures

5.1 Introduction

This chapter presents the experimental characterization methods and procedures used to carry out the work reported here. Development of the ANN models and use of the difference correction functions are discussed.

5.2 Methodology

The aim of the proposed research was to design, develop and characterize a low-cost photodiode-based radiometer to be used for prolonged renewable energy studies. The radiometer was designed using a diode connected to a transimpedance amplifier. The solar irradiance measurement station is installed on the rooftop of the Faculty of Agriculture, Science and Technology building of North-West University, (latitude $25.86^{\circ}S$ and longitude $25.64^{\circ}E$). The photocurrent produced by incident light is converted into a voltage using a feedback resistor. The designed instrument and the CMP11 reference were both connected to 34970A data logger using two separate channels. Daily measurements were recorded at 10 s intervals for a period of up to six months. Data for the portion of the study pertaining to global horizontal irradiances were collected under all sky conditions

for a period of about six months. Measurements were regularly retrieved and saved as an excel (*.xlsx*) file into a folder named after that month. Appendix A shows a typical excel file for a particular summer day. As the data logger recorded voltage measurements even during the night there was need to remove night time data before the analysis. Each daily file was labelled using the day of the month when that data was collected (e.g., *June23.xlsx*). Daily measurements were then read into a Matlab script. CMP11 voltages were converted into irradiance by dividing the measured voltage with the sensitivity factor S . Measurements collected during June-July time are referred to as winter, while those from August to November constituted summer. Two artificial neural networks (one for summer and one for winter) were developed with BP21 voltages as inputs and CMP11 converted irradiances as the target. The models were tested and validated. Irradiances estimated using photodiode measured voltages were then compared with the expected or CMP11 measured irradiances. Signals measured by the BPW21R photodiode will herein be simply referred to just as BP21 signals.

The method used could be broadly summarized in a sequence of steps as :

- design and construct a transimpedance based Si-photodiode radiometer.
- connect the radiometer and CMP11 reference pyranometer to the data logger.
- measure and save daily voltages to a file for calibration purposes.
- download data and extract day time measurements.
- design and train an artificial neural network (ANN) using a portion of the data recorded data.
- test the network using known inputs and outputs for selected days and compare results.
- correct for any existing mismatches and compare again.

5.3 Irradiance estimations using artificial neural networks

The calibration of a photodiode sensor that suffers from non-linearities and spectral mismatch is done using an artificial neural network (ANN). Neural networks provide a new tool for the fast solution of repetitive nonlinear curve fitting problems. In this work the concept of a neural network is introduced, and it is shown how such networks are used for fitting functional forms to experimental data. For applications like the one reported here, that generate high volumes of data, the neural network approach automates the curve fitting process that can operate at high speed [50]. This allows the estimation of solar radiation intensity from the recorded BP21 photodiode recorded voltages without the need for a reference. The first step in the development of ANN model is to train the ANN model with experimental data. After training of the ANN model, the optimal ANN configuration is determined. Finally, the ANN model is validated with data, which is not used in the training. The main goal of the study is to develop the most optimal ANN model for the estimation of solar irradiances from the measured photodiode voltages. The feed-forward back-propagation network structure was used in this application.

A neural network is a mathematical function with a number of parameters that are fitted in a way so that difference between the target and neural network output MLP is minimized for the given set of input-target pairs for training. It is also possible to generate clear-sky irradiance from a set of astronomical and weather parameters using artificial neural networks (ANNs). The ANNs approximate the functional relationship between random input and output variables by learning from examples made up of historical data output and input variables. One major attraction of ANN methods is their ability to find relations between input and output even if the representation was intractable. The ANN can,

therefore, map a wide range of possible combinations of input or explanatory variables to a single desired output. This, however, does not underplay the importance of carefully selecting the variables.

The basic problem in curve fitting is to find N parameter values $a_1, a_2, \dots, a_N$ associated with the function $E(\lambda; a_1, a_2, \dots, a_N)$ which best represents the underlying trends in a set of N data points [50]. Once trained, the network can rapidly perform the curve fitting process on new data. A neural network provides an attractive approach for repetitive curve fitting problems that involve experimental data. While the training of such networks can be computationally intensive, a trained network can process new data rapidly. The ANN used here employs a feed-forward back propagation technique. Figure 5.2 shows a flowchart used for developing a MLP network for predicting daily solar irradiances. Training of the network was done using a portion of the 6 months of BP21 measured data as the input and the CMP11 measured irradiances as the target. Once the network has been saved to a file, we only do steps in the dashed green box on the BP21 measured data, to calculate the expected irradiance as illustrated in Fig. 5.1.

In summer, day time is longer than in winter. Summer daytime measurements were recorded at 10 s intervals from 06:00 to 18:00 hrs local time, giving a total of 4321 samples a day. In winter, measurement commenced at 06:00 and lasted until only 16:30 hrs giving a total of 3786 samples. Any attempt to try and match the sample sizes for the two seasons will result in either appending zeros from 16:30 to 18:00 winter data, or truncating the summer measured data. Doing either of the two will inevitably lead to an inaccurate ANN. So two separate networks were developed, one for summer and another for winter. Testing and validating developed networks was done using data for selected days. Figures 5.2 and 5.3 show block diagrams that summarize how global irradiances for

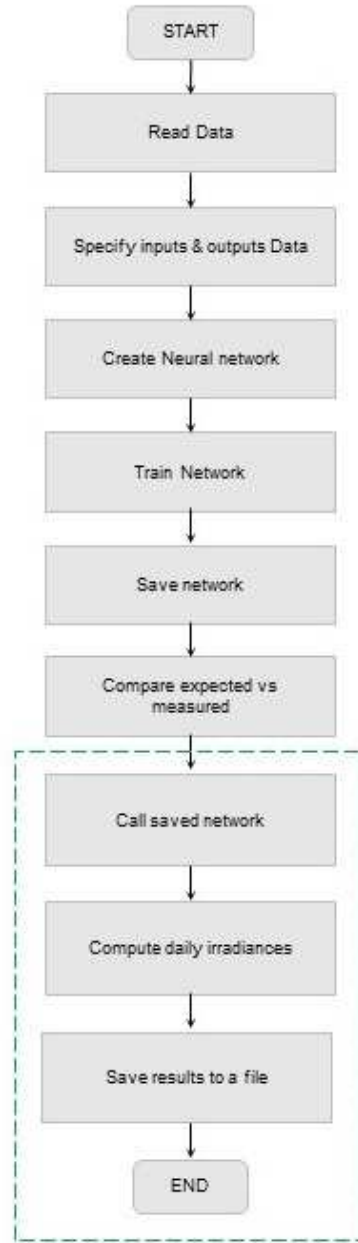


Fig. 5.1. Flowchart for developing a multilayer perceptron network for calculating solar irradiances.

the entire day were estimated from BP21 measured voltages for winter and summer time, respectively. Figure 5.4 shows a block diagram that summarizes the method employed in this study. CMP11 voltages were first converted into irradiances using a sensitivity factor specified by the manufacturer. BP21 voltages were input into the Levenberg-Marquadt ANN, while the CMP11 measured irradiances were the targets. After the training, BP21



Fig. 5.2. Block diagram showing how to estimate irradiances from winter BP21 measured voltages.



Fig. 5.3. Block diagram showing how to estimate irradiances from summer BP21 measured voltages.

voltages measured on selected days were used to test the networks. This resulted in ANN estimated irradiances that were compared against CMP11 measured. Differences between CMP11 and ANN estimated irradiances resulted in a difference correction function (dcf) for that period. The dcf was simply added to any ANN estimated irradiances to give difference corrected, ANN estimated (dc ANN BP21) irradiances, which were compared again to the CMP11. Root-mean square errors and correlation coefficients were used to quantify any further differences in the final irradiances.

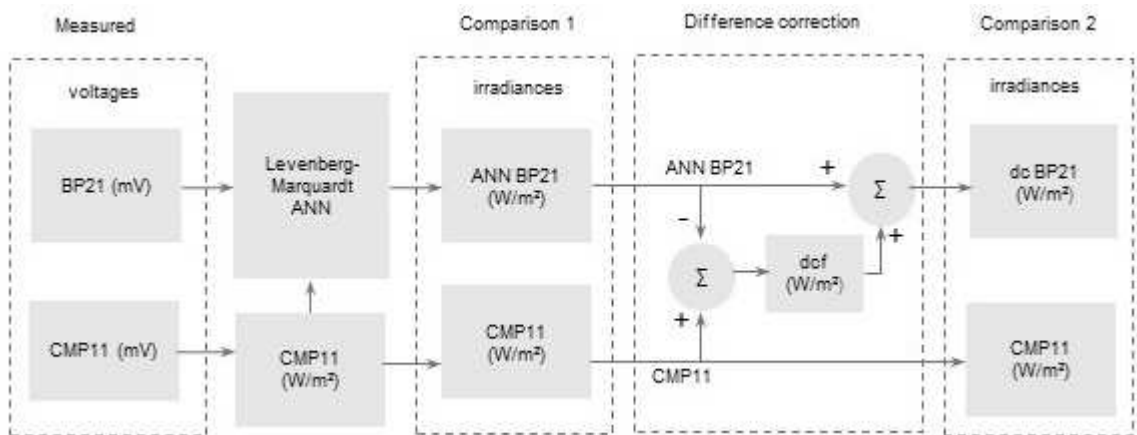


Fig. 5.4. Block diagram summarizing the method used to study measured voltages.

Chapter 6: Experimental results and discussion

6.1 Introduction

In this chapter, results of the characterization and ANN estimated irradiances are presented together with the results of the correlation. A major part of the measurements was taken during winter and summer period. This chapter concludes with an assessment of the radiometer performance both before and after the difference correction method was used.

6.2 Spectral response of the photodiode

The BP21 diode photocurrent produced by a given level of incident light varies with wavelength. This wavelength response relationship is known as the spectral response characteristic and it is expressed numerically in terms of radiant sensitivity or quantum efficiency. The BP21 radiometer will be calibrated against the CMP11 secondary standard so it is important to first show how the spectral responses compare. Figure 6.1 (a) shows the spectral response of the BP21 photodiode and Fig. 6.1 (b) shows the BP21 response when compared to the CMP11 reference pyranometer response. There is a problem of spectral mismatch between the two devices. Whilst the CMP11 has a flat spectral response

over the entire solar spectrum, the BP21 has a confined spectral response in the visible part of the solar spectrum extending just from 300 nm to 750 nm. As shown in Fig. 6.1 (a), the silicon detector provides no response to radiation in the near-UV (NUV, 300 - 380 nm), and has an almost linearly increasing response in the visible (VIS, 380 - 560 nm). The diode response decreases from 560 to 750 nm and then no response to the rest of the near-infrared (NIR, 750 - 4000 nm). The spectral distribution of visible solar radiation reaching the ground is not constant but varies with air mass, cloud cover, turbidity, atmospheric water vapor content, and the reflective characteristics of the ground's surface [4].

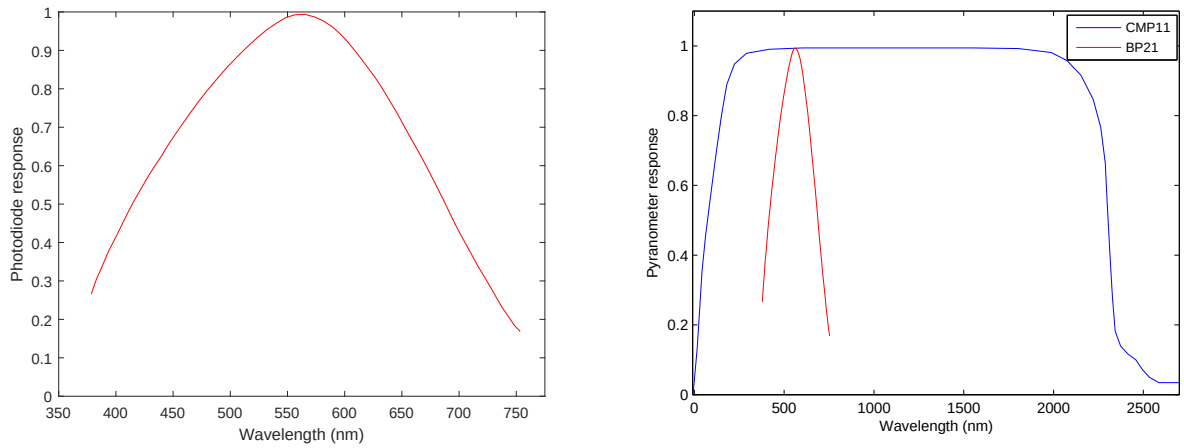


Fig. 6.1. Spectral response of (a) left- BP21 diode (b) right - BP21 in relation to CMP11.

6.3 Daily measured voltages

Figures 6.2 and 6.3 show voltages measured by the two devices on clear and partly cloudy days in winter, and summer, respectively. The effects of the mismatch are evident. Whilst the CMP11 measured voltages have a dome shape for both periods, the BP21 measured appear to have a Gaussian shape. While there are evident day-to-day fluctuations in the measured voltages from winter to summer, attributed to atmospheric variability, there is no indication of a substantial variation from the characteristic shapes observed. This leads

to the conclusion that the two devices maintained quite good stability over the 6-month observation period.

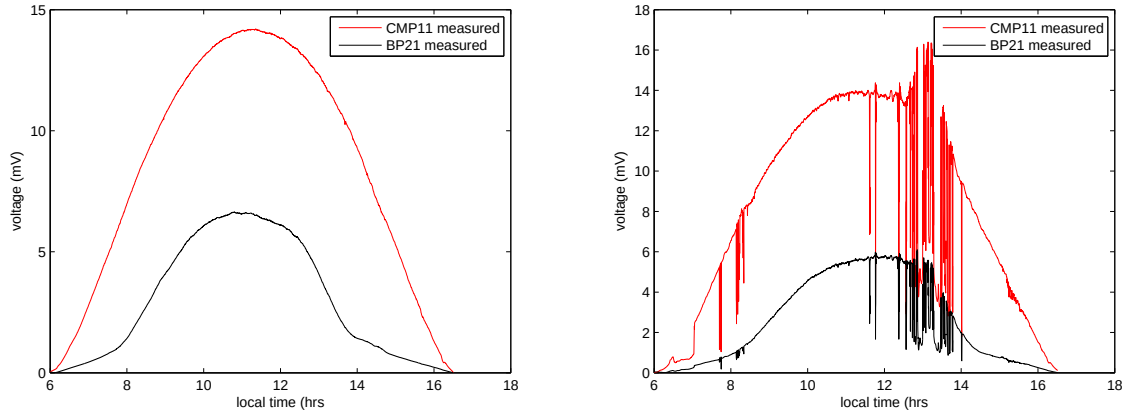


Fig. 6.2. CMP11 and BP21 measured voltages in winter on (a) left - clear day, 5 June (b) right - partly cloudy day, 16 June 2017.

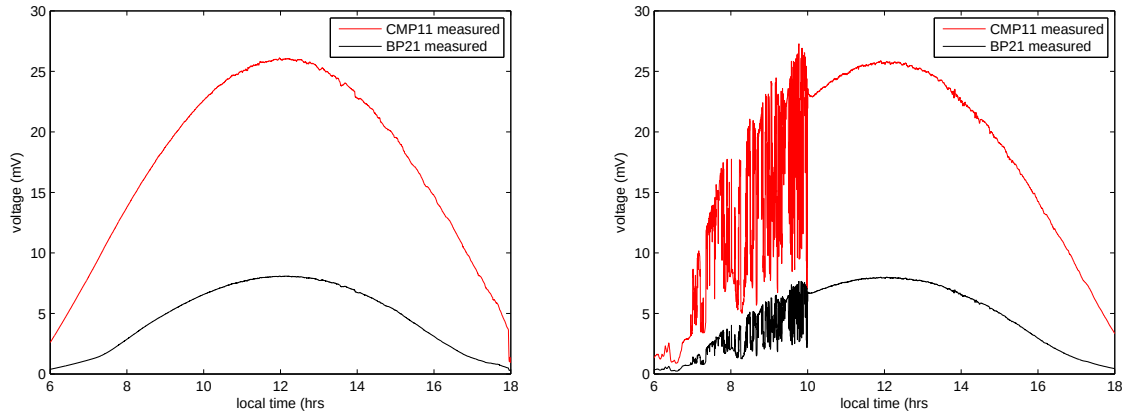


Fig. 6.3. CMP11 and BP21 measured voltages in summer on (a) left - clear 30 Nov (b) right - partly cloudy day, 2 Nov 2017.

Figure 6.4 shows typical daily correlations between the CMP11 and BP21 measured voltages measured on clear summer day (Fig. 6.3(a)), and winter day (Fig. 6.2(a)), respectively. In both graphs, the green line shows measurements from morning (06:00 hrs) to solar noon, while the black plot (top to bottom) show voltages measured from solar noon to evening. The correlation observed during the winter period is worse than that for summer between 08:00 hrs to 14:00 hrs. Figure 6.4 (b) shows some hysteresis in the

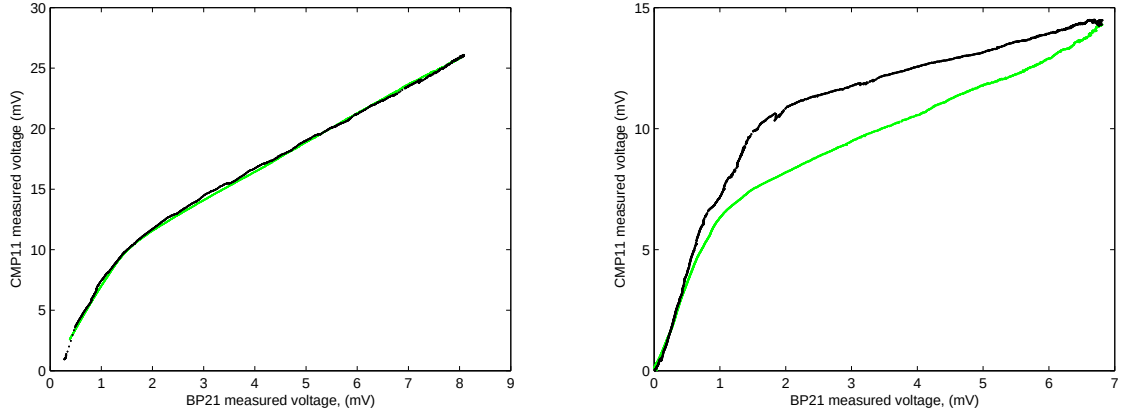


Fig. 6.4. Typical correlations between CMP11 and BP21 measured voltages on clear (a) left - summer day, (b) right - winter day.

measurements with and a knee at around 1.0 mV photodiode voltage. This could be explained by the fact that unlike the CMP11 pyranometer detector with a viewing angle or field of view (FOV) of 180° , the photodiode is flat so has a reduced viewing angle. This means the photodiode mainly receives diffuse radiation at high zenith angles that are in the morning and evening. Morning radiation mainly constitutes of UV and VIS, afternoon is mainly VIS and for late afternoon the radiation is mainly IR and VIS. As the CMP11 has a flat spectral response over all solar wavelengths, results shows that the BP21 has different responses for morning and afternoon wavelengths. For example, when the incident radiation gives a CMP11 voltage of 10 mV in winter, the BP21 gives a reading of about 4.5 mV in the morning and around 1.5 mV in the afternoon. This gives rise to the observed hysteresis. The two devices have different spectral responses that is why the relationship is non-linear. For the design to successfully track the reference CMP11, its correlation coefficient to the CMP11 should be as close to 1.0 as possible. To achieve this, ANNs were used and signal processing techniques were applied to daily measured voltages so as to match the two devices.

Figure 6.5 compares typical daily winter and summer voltages measured by the BP21.

Morning and afternoon measured voltages relate differently for the two seasons. In addition, summer time has more radiation hours compared to winter. Voltages measured beyond 16:30 hrs were close to zero because of shorter winter days time in this region. This suggests that a single ANN model cannot be developed and used to correctly predict irradiances for both these two seasons. Voltages were measured as a function of time of day. So, although time is not directly used as an input in the developed networks, the nature of the data used in the training makes the network differentiate between morning and afternoon measurements. If the BP21 voltage is to be matched to the CMP11, then different weights have to be applied to the BP21 data at each time of the day or measurement. This is a huge problem because the weights required for matching vary every day. Instead, artificial neural networks were employed to circumvent this cumbersome procedure. The ANN is used as a pattern associator that will be here trained to perform the mapping between the sensor's readings and the reference signal measured by the CMP11 standard pyranometer. Thus the ANN will be able to predict the expected irradiances from the BP21 voltage readings.

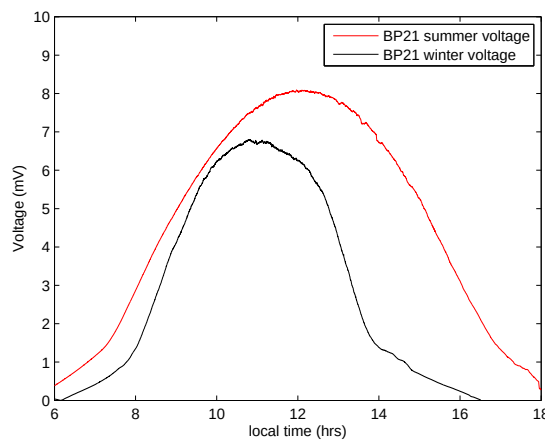


Fig. 6.5. Comparison between typical summer and winter voltages measured by the BP21 photodiode.

6.4 ANN estimated irradiances

The CMP11 voltage signals were converted to solar radiation units by simply dividing it by a sensitivity value of $S = 9.38 \mu V/(W/m^2)$.

$$E_{\lambda} = \frac{V_{cmp11}}{S} \quad [W/m^2] \quad (6.1)$$

Then BP21 measured voltages were used as inputs to the developed ANN models while CMP11 measured irradiances were the targets. The objective was to use ANN models to linearise the responses shown in Fig. 6.4. The biggest challenge came when dealing with the winter measured voltages as it is evident that further corrections would be required after ANN estimations.

In this section, irradiances estimated from BP21 voltages using ANN network are presented and compared against CMP11 measured irradiances for both summer and winter. As seen previously, summer measured voltages results have a dome shape from about 0:800 hrs to about 16:00 hrs while for winter the dome shape is observed from about 08:00 hrs to 14:00 hrs. In addition, day time is longer in summer compared to winter. In summer, measurements were recorded from 06:00 hrs to 18:00 hrs giving 4321 ten-second samples, while in winter measurements commenced at 06:00 hrs until 16:30 hrs giving 3786 measurements. So using summer and winter measurements with different sample sizes to train a single ANN network will not result in a good network. Appending 0.0 mV voltages from 16:30 to 18:00 hrs winter time will not help either. This explains why a single ANN model cannot work for the entire measurement period recorded here. Two separate networks were developed and used to predict irradiances from the BP21 measured voltages. It is important to note that signals measured on partly cloudy days were not used for developing the ANN models because of huge variations and errors they intro-

duce. However, when developed models are applied to these days, the irradiances show good correlation. Comparison of the CMP11 measured and ANN estimated irradiances are presented for selected days for both summer and winter times. Voltage correlations, ANN estimated irradiances and CMP11 measured are also presented for selected days for both summer and winter times. The first plotted row of Fig. 6.6 shows non-linear voltage correlations in summer on clear and partly cloudy days, respectively. The BP21 measured voltages presented in Fig. 6.6 were input into the trained ANN network whose output is compared against the CMP11 measured irradiances as presented in row 2 of Fig. 6.6, for the respective summer days. Fig. 6.7 presents the correlation results between the CMP11 irradiances and the ANN estimated for two other summer days. For all the summer days the presented correlations are reasonably close to the expected.

Figure 6.8 shows ANN estimated irradiances on both partly cloudy and clear days during winter time. As can be observed mismatches are not pronounced at low irradiances (lower than 300 W/m^2). These results consistently show a shift in the ANN estimated peaks relative to the CMP11 peak. As the photodiode peak appears before the CMP11 peak, this could be explained as being due to a small East ward tilt on the photodiode relative to the horizontal. Tilt effects are usually caused by practical limitations on how accurately the radiometers can be mounted level with respect to the horizontal platform on which they are mounted. Winter results show that BP21 measured irradiances are consistently observed to lie above the CMP11 measured from morning up to solar noon, while from solar noon to evening BP21 readings are less than CMP11 measured.

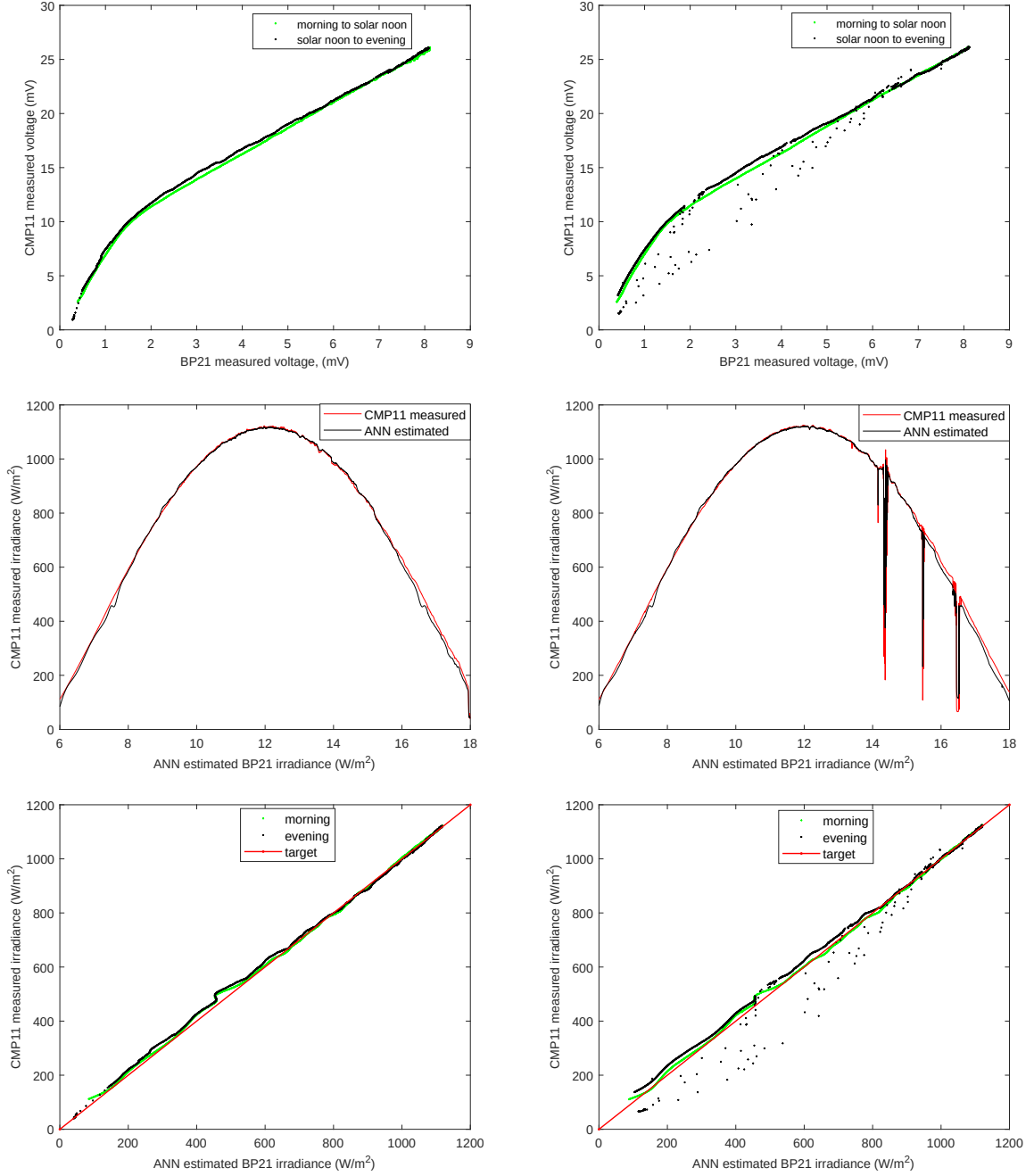


Fig. 6.6. Comparison of CMP11 and BP21 signals in summer on clear day, 30 Nov, (left column) and partly cloudy day, 10 Oct (right) : (row 1 - voltages , row 2 - CMP11 irradiances and ANN estimated, row 3- irradiance correlation).

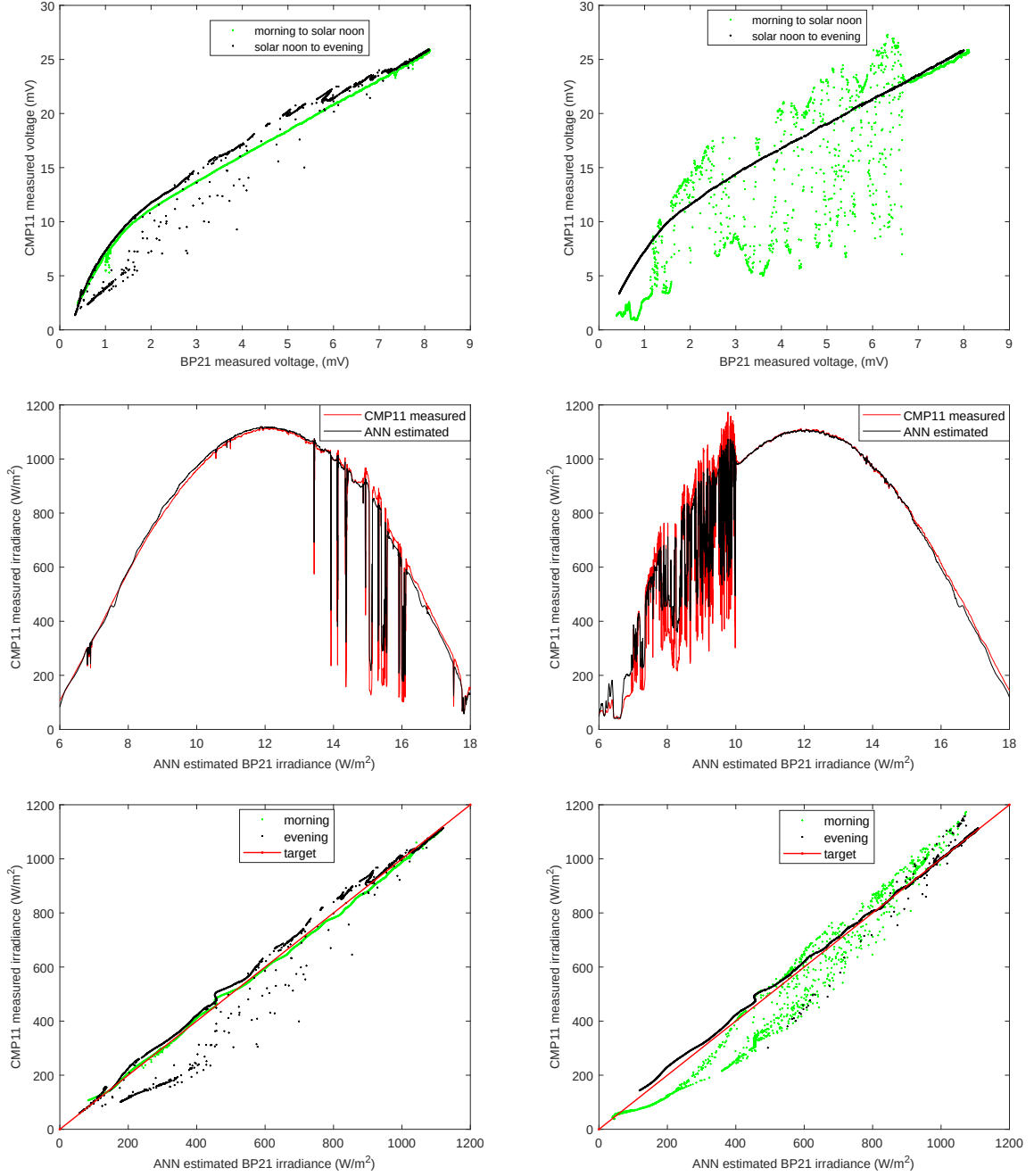


Fig. 6.7. Comparison of CMP11 and BP21 signals in summer on clear day, 8 Sept, (left column) and partly cloudy day, 2 Nov (right) : (row 1 - voltages , row 2 - CMP11 irradiances and ANN estimated, row 3- irradiance correlation).

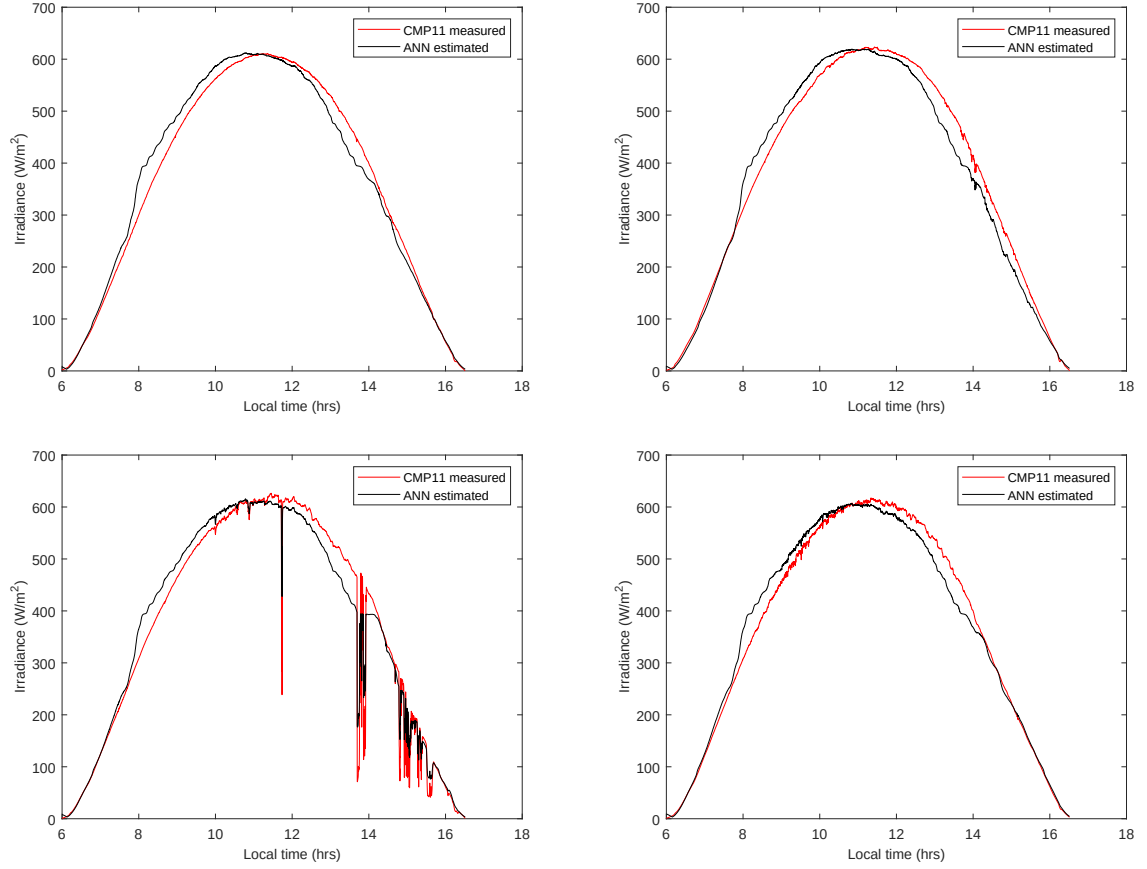


Fig. 6.8. Comparison of CMP11 measured and the ANN estimated BP21 irradiance in winter of 2017 : row 1 - 5 June and 13 June, row 2 - 16 July and 27 July.

As the Earth orbits around the sun, it rotates clockwise about its axis, from west to east that is why the sun rises in the east and sets in the west. But to an observer on Earth, it is the sun that seems to be revolving around the Earth. From this point of view, it is important to have an understanding of the path followed by the sun in its daily and annual movement across the sky as observed from Earth. Figure 6.9 shows different trajectories followed by the sun during different seasons as perceived by an observer on this part of the Earth. The sky can be conceived as being a hemispherical shell covering the plane on which we stand. During the course of a day, the sun is observed to follow a circular arc which is symmetrical about the vertical plane running north and south through the observing position. At solar noon, the sun occupies its greatest altitude for the day. The

red line shows the trajectory followed by the sun during summer time, while the blue shows the sun trajectory during winter time. Unlike winter trajectory, in summer the sun trajectory passes directly overhead, so most of the radiation received on a horizontal surface during this period is direct.

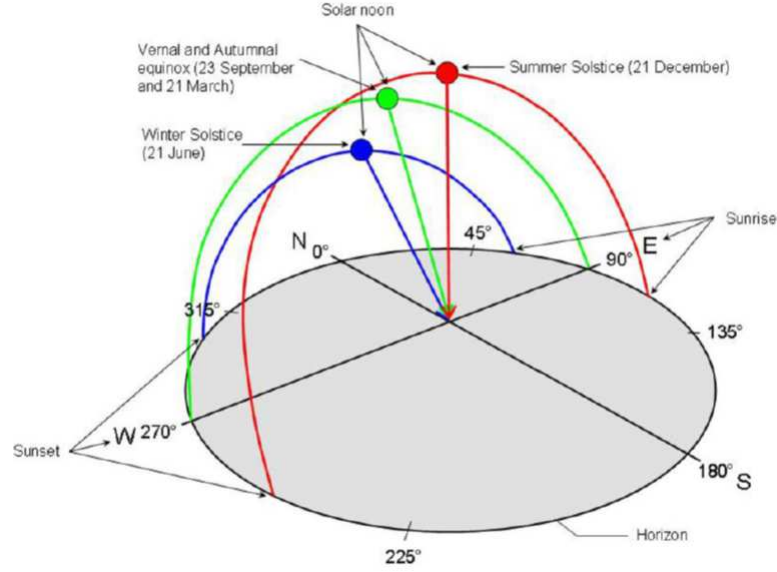


Fig. 6.9. Sun's apparent path in the sky during different seasons (Pretoria)([CSIR 2010](#)).

Figure 6.10 shows surface angles used in solar radiation studies. These angles are calculated based on a specified mounting and orientation of the solar collector or radiometer. Tilt angle, β is the angle between the plane surface and the horizontal (with $0^\circ < \beta < 90^\circ$ for a surface facing towards the equator; $90^\circ < \beta < -90^\circ$ for a surface facing away from the equator). Solar azimuth angle, z is the angle between the solar beam and the longitude meridian. The surface azimuth angle, Z_s defined as the angle between the normal to the surface and the local longitude meridian. Sign convention is as for z . For a horizontal surface, Z_s is 0° always. Angle of incidence is the angle between solar beam and surface normal. Solar zenith angle, ϕ is the angle between the solar beam and the normal to the horizontal.

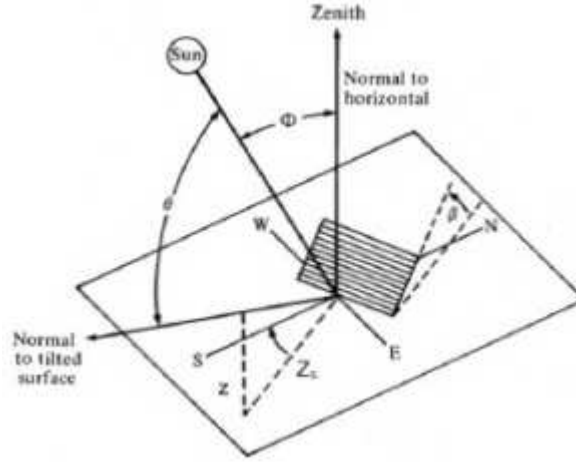


Fig. 6.10. Zenith angle, angle of incidence, tilt angle β , solar azimuth angle, z and surface azimuth angle, Z_s , for a tilted surface [51].

Results presented in row 1 of Fig. 6.11 are typical measured voltage correlations for summer and winter, respectively, that have already been discussed. Row 2 of Fig. 6.11 shows the correlation between the ANN estimated irradiances against the CMP11 measured for summer and winter time, respectively. Results show that solar spectral radiation that has been proportionately shifted toward the red and near infrared, such as under conditions of high air mass, is overestimated by the photodiode radiometer, while solar spectral radiation shifted toward the near ultraviolet and blue end of the spectrum, such as under partly-cloudy skies, is underestimated by the radiometer. In both row 2 plots of Fig. 6.11, red graphs represent the target correlation that is expected if the two instruments are to be matched. Correlation results for summer irradiances are not as bad as those observed for winter. This could be explained from the different sun trajectories presented in Fig. 6.9.

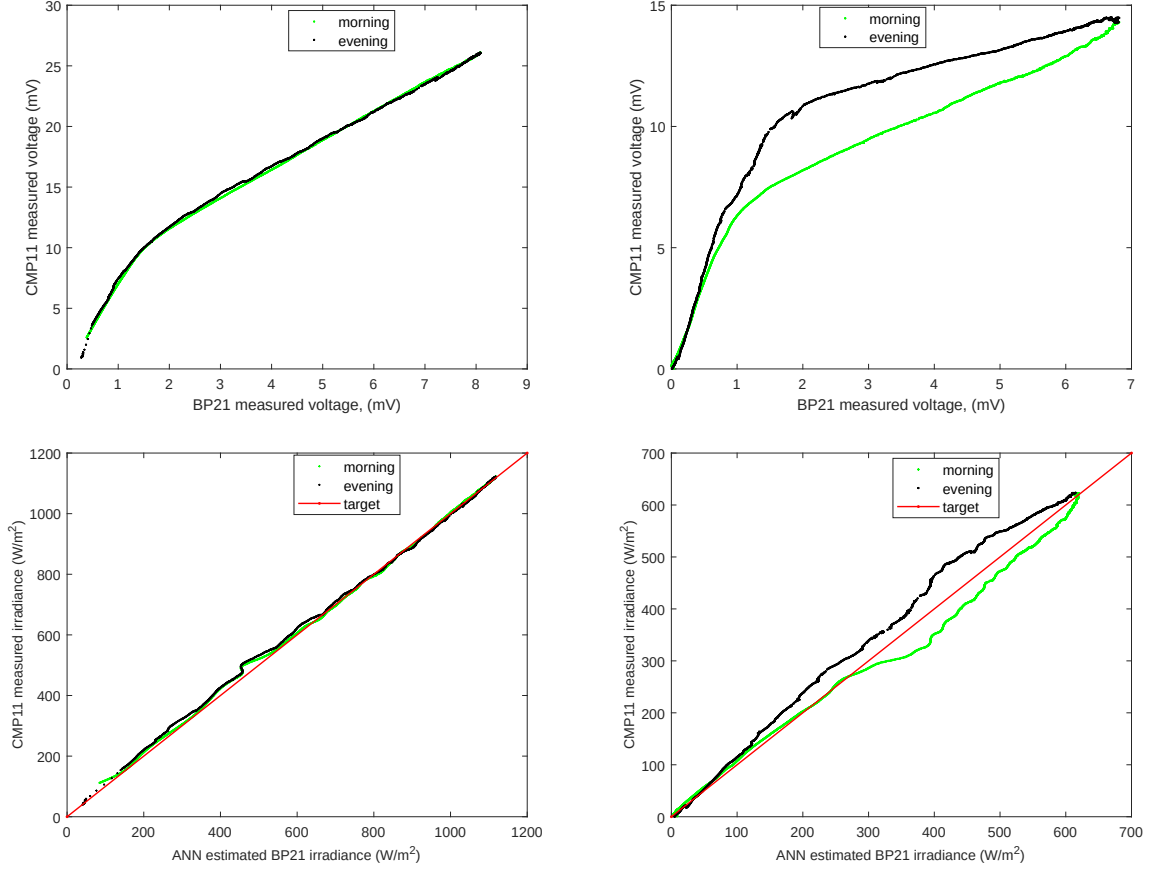


Fig. 6.11. Comparison of daily correlation between CMP11 and BP21 signals : left column - summer day, right column - winter day, row 1 - voltages, row 2 - irradiances.

6.5 Possible photodiode tilt in winter

For solar irradiance measurements, radiometer sensor responses to radiation should vary with the cosine of the angle of incidence from a line vertical to the surface of the sensor [22]. The difference between the radiometer response and the ideal cosine response is termed the cosine error. The pronounced winter mismatches between ANN estimated and CMP11 measured irradiances could also be due to the cosine response error of the photodiode. The cosine response error at large solar zenith angles is intrinsic and variable with instrument types and manufacturers. Stroeve et al.,[52] observed deviations of their designed pyranometer from a highly accurate instrument to be in excess of 5 % at solar

zenith angles larger than 75° . [Van den Broeke et al., \[53\]](#) obtained negative net shortwave radiation at high solar zenith angles using Kipp & Zonen CM3 pyranometers. [Wang et al., \[54\]](#) reported that according to the manufacturer's report, the typical percentage deviation of a Kipp & Zonen CM3 pyranometer from the ideal cosine behavior is $\sim 2\%$ at a solar zenith angle of 80° , with a maximum of $\sim 8\%$.

Measurements presented here assume that the two instruments are horizontally oriented, i.e. parallel to the (flat) Earth surface. Winter estimated ANN irradiances (Fig. 6.8) consistently show a shift in the ANN estimated peaks relative to the CMP11 peak. As the photodiode peak appears before the CMP11 peak, this could be explained as being due to a small eastward tilt on the photodiode relative to the horizontal. The tilt angle has a major impact on the solar radiation incident on a surface. Tilt effects are usually caused by practical limitations on how accurately the radiometers can be mounted level with respect to the horizontal platform on which they are mounted. Unlike the CMP11 reference pyranometer, the designed radiometer has no spirit level for horizontal level settings. As a result of this, it is difficult for the eye to observe small tilt angles if they exist. It is here suggested that the differences observed during winter could be due to tilt. During summer, however, tilt effects are not so pronounced in summer. This may be because of the trajectory followed by the sun. Results also show that tilt effects that result in the observed shift in the peak irradiances are more pronounced in winter than in summer. This may be because during summer, the sun trajectory passes directly overhead so most of the received radiation is direct. Both CMP11 and BP21 measure peak values at normal angles of incidences. Looking at Fig. 6.8, starting from morning, the BP21 sees its (solar noon) normal incidence radiation earlier than the horizontally oriented CMP11. For this time, the reference irradiances are less than the ANN estimated results. In the afternoon, the reverse is observed, with BP21 measured voltages below the CMP11. This

implies that there is a tilt on the BP21 towards the east. Mafikeng weather is characterized by strong, dusty winds during the winter periods. It is possible that during occasional cleaning of dust from the photodiode may have caused some tilt. On average, the time delay between the signals shown in Fig 6.8 is about 30 minutes (0.5 hrs). The Earth takes 24 hrs to rotate 360° . This means that in 0.5 hrs, the Earth has rotated $\beta \sim 7.5^\circ$. This means that winter irradiance measurements reported here may have been taken when the BP21 photodiode was tilted by $\sim 7.5^\circ$ relative to the horizontal.

For a fixed tilt angle, the maximum power over the course of a year is obtained when the tilt angle is equal to the latitude of the location. The purpose of applying a tilt correction is to modify the measured irradiances such that they well represent the horizontally oriented value of global horizontal solar radiation. The primary source of the bias in solar radiation measurements is the instrument leveling (i.e., sensor tilt) ([53], [55]). Tilted sensors will result in either underestimates or overestimates of radiation measurements, depending on the combination of the tilt angle and tilt direction. As pointed out by [Van den Broeke \[53\]](#), theoretically, a tilt angle of 1° towards the north will induce a $\sim 20 \text{ Wm}^2$ bias in net solar radiation. Using a radiative transfer model, [Bogren et al., \[56\]](#) estimated the albedo error introduced by a station tilt of 5° to be $\sim \pm 13 \%$. In order to obtain accurate radiation on a horizontal surface at all times it is important is to correct for tilt. In order to determine how much tilt there is, some researchers suggest that information on latitude, longitude, pitch, roll, and heading is needed. Others suggest that in order to apply the correction for tilt, the measured irradiance has to be first partitioned into direct and diffuse portions. Yet even others suggest that there is need to know various angles and the position of the sun at each time of the different days. Measurements here are made every 10 s, so in this case it would require the knowledge of the sun position every 10 s.

6.6 Daily irradiance deviations

To ameliorate possible photodiode tilt biases in the measured irradiances, a new method herein called *daily irradiance deviations* method is introduced, that depends only on the differences between ANN estimated and CMP11 measured irradiances and no additional instrumentation. ANN estimated irradiances show some significant differences (referred to as deviations) when compared against the CMP11 expected irradiances, especially for the winter period. Row 2 of Fig. 6.11 shows typical correlation between CMP11 and ANN estimated irradiances for a typical summer and winter day, respectively. If ANN estimated irradiances are to perfectly match the CMP11 measured, then the correlation should lie on the bold red line. So the aim is to adjust both black and green correlation lines shown in the figure so that they both lie as close to the red line as possible. Column 1 of Fig. 6.12 shows correlation of ANN estimated and CMP11 measured irradiances for selected winter days, while column 2 shows the corresponding deviation functions. All the figures appear to be antisymmetric around 11:30 local time. First, daily deviation functions were obtained using daily ANN estimated irradiances and corresponding CMP11 irradiances for summer and winter separately. The method employed to correct for morning overestimates and afternoon underestimates involves the use of a deviation function that calculates how far each point lies away from the expected points on the red line. These deviations were obtained from the simple difference between the ANN estimated irradiances and the CMP11 measured irradiances. Figure 6.13 shows daily deviation functions for selected days together with the average deviation, with left showing summer deviations and right showing winter deviations. The deviation functions show how much each ANN estimated irradiance deviates from the expected CMP11. Both summer and winter deviations consistently show similar persistent form. For all winter

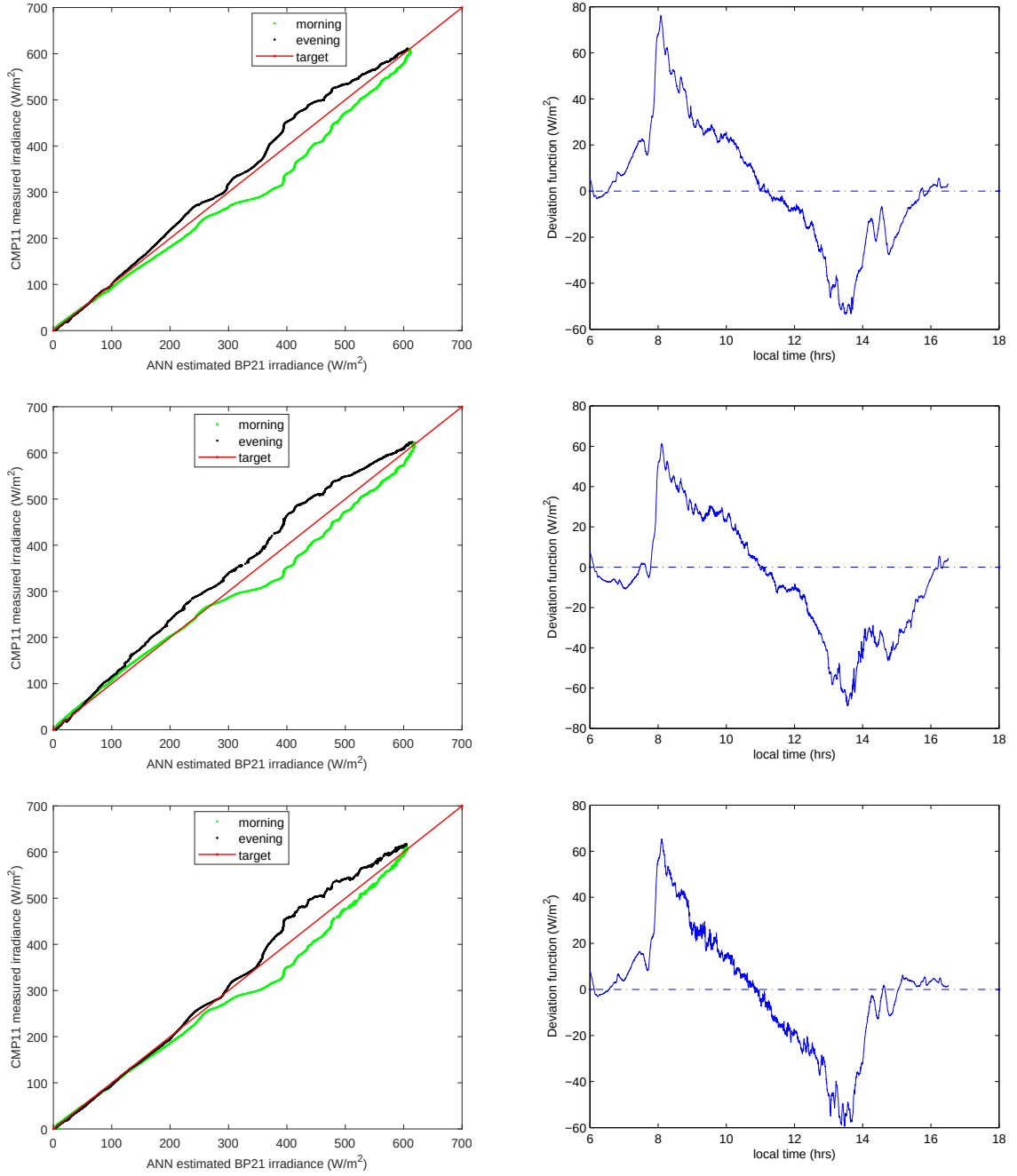


Fig. 6.12. Left column-Typical correlation of ANN estimated and CMP11 measured irradiances in winter, right column - corresponding deviations functions.

days, the deviations are observed to be almost linear between 08:00 hrs and 13:30 hrs local time, with peak deviations observed around these specific times. Averaging the deviation functions over the number of days gave the average deviation function for that season. Averages for both seasons are shown as black line in both plots. An attempt is

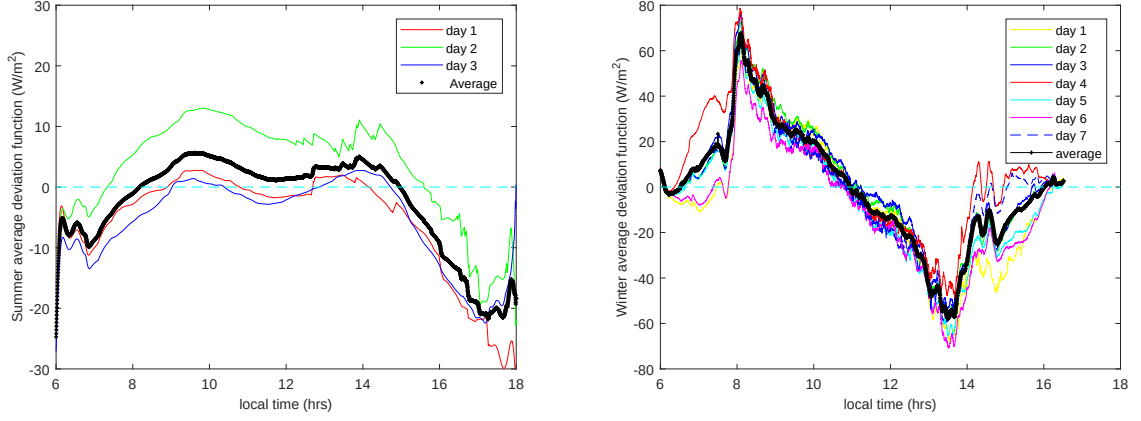


Fig. 6.13. Daily deviation functions for selected days and the average deviation (in bold black) (left) - summer (right) - winter.

presented in later sections, to explain the observed differences in the deviations for the two seasons.

6.7 Difference correction functions (dcf)

Since the objective is to match ANN estimated and CMP11 measured irradiances, average deviation functions presented above were negated to produce the average difference correction functions (dcf). The difference correction function was implemented to bring the ANN estimated irradiances on the red line that corresponds to a correlation value of 1.0 as previously discussed. The average difference correction function removes varying excess amounts of ANN estimated radiation in the morning, while adding different amounts to the underestimated evening irradiances. Any ANN estimated irradiances are simply corrected by adding the corresponding average difference correction function for that period. Figure 6.14 shows average difference correction functions required for correcting summer and winter ANN estimated irradiances. Recall that these functions were obtained by negating average deviation function presented in Fig. 6.12. They both show

by how much the ANN estimated irradiances should be adjusted to match the CMP11 measured irradiances. The dcfs were developed using irradiances taken on sunny days for both summer and winter periods. However the corrections worked so well when the computed averages dcf were applied to partly cloudy estimated irradiances as shown in results presented in sections 6.7 and 6.8.

Average deviation functions for both seasons were estimated using insolation obtained on clear days in that season and were used to adjust radiation of that whole season. As pointed out by Zhandire [57], clear-sky conditions present atmospheric conditions that produce predictable effects on solar irradiances. While the winter average dcf is nearly symmetric around solar noon (1200 hrs local time), the average winter one is antisymmetric around 1130 hrs local time. The differences in time may be attributed to the different trajectories followed by the sun during the two seasons or is because of the tilt suggested earlier. There is however no other apparent plausible explanation to explain the observed differences in the dcf at this stage. Summer average deviations vary between $+15 \text{ W/m}^2$ and -40 W/m^2 . Peak variations are observed in the morning and late afternoon times, while least deviations were observed between 10:00 hrs and 14:00 hrs. For winter, average deviations required to correct ANN estimated irradiances were

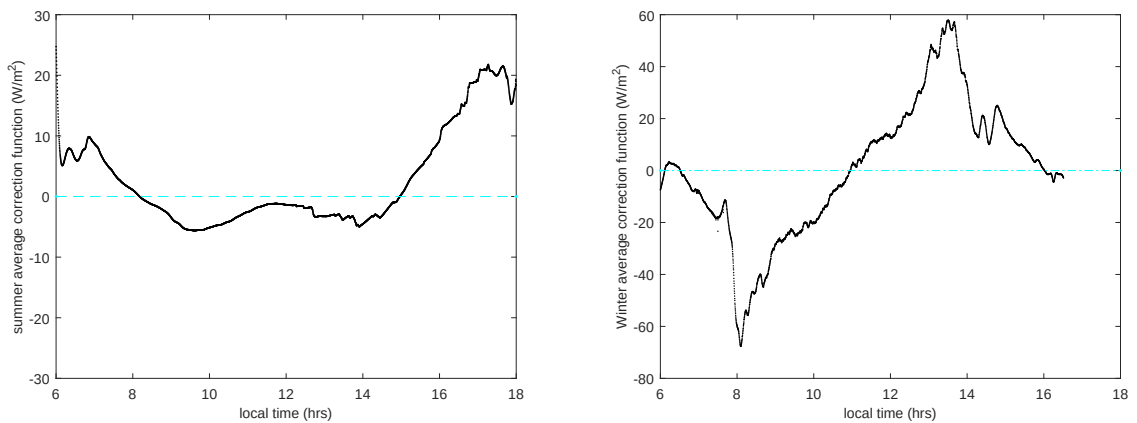


Fig. 6.14. Average difference correction functions for summer (left) and winter (right).

observed to be between -60 W/m^2 (morning) and $+60 \text{ W/m}^2$ (late afternoon).

The following MATLAB script shows how the correction function was derived from the deviations and used for further correcting any ANN estimated irradiances :

% Difference correction function, dcf

```
%
[mx idx] = max(CMP11);           % check for highest CMP11 reading and get the index
mc = -(ANNBP21(1:idx)-CMP11(1:idx)); % morning correction - from morning to CMP11 solar noon
ec = CMP11(idx+1:n)-ANNBP21(idx+1:n); % evening correction from CMP11 solar noon to evening
diffcorr = [mc, ec];             % merge into one correction function for entire day
save diffcorr;                   % save the dcf or later use with any ANNBP21 estimated data
corrANN = ANNBP21 + diffcorr;    % correct for any winter measured data
%
```

The difference correction function routine (presented above) was used for developing both summer and winter difference correction functions. Figure 6.13 shows the respective average deviation function for summer and winter, while Fig. 6.14 shows the average difference correction function required to match the ANN estimated with the CMP11 irradiances for summer and winter periods, respectively. The average deviation function shows how much the ANN estimated irradiances differ from the CMP11 measured irradiance for both morning and afternoon times. Difference correction functions are simply obtained by negating the corresponding average deviation functions.

To be able to identify other signals related to the derived winter correction function, we first look at the logistic sigmoid function that was used as the activation function for the development of the ANN network.

A logistic sigmoid function is one of the activation functions used in ANN and is defined as :

$$sg(t) = \frac{1}{1 + e^{-\beta t}} \quad (6.2)$$

where β represents the slope of the sigmoid function and t is time of day with $t = 0$ corresponding to 06:00 hrs. The unipolar sigmoid function is a continuous non-linear function, which maps an infinite input domain $(-\infty, \infty)$ to a finite output domain : $(0,1)$. Setting $\beta = 1$, the first derivative of Eqn. (6.2) is expressed as :

$$sg'(t) = \frac{1}{1 + e^{-t}}(1 - \frac{1}{1 + e^{-t}}) \quad (6.3)$$

which be written as :

$$sg'(t) = sg(t)(1 - sg(t)) \quad (6.4)$$

and the second derivative can be written as :

$$sg''(t) = sg(t)(1 - sg(t))(1 - 2sg(t)) \quad (6.5)$$

The sigmoid function was used as the activation function for neural networks developed in this study. This function is commonly used for ANN design with back propagation training [58]. Back propagation algorithm is based on gradient decent which requires calculating the differential output of the activation function. Figure 6.15 shows plots of the logistic sigmoid function, its first and second derivatives together with the negated second derivative. The logistic sigmoid function has a characteristic 'S' shape that is essentially linear in the center and non-linear toward their bounds that are approached asymptotically. All winter daily deviations presented in Fig. 6.13 (b) show characteristic features that resemble the second derivative of the sigmoid function, with antisymmetry around 11:30 hrs local time.

Figure 6.16 shows the sigmoid first derivative (Gaussian) and its negated derivative. Figure 6.17 shows a typical plot of BP21 measured voltages alongside the negated first derivative of the voltages, averaged over an hour. This average is observed to be close to the negated sigmoid second derivative. These results show that winter measured BP21 voltages almost have the same waveform as the first derivative of the sigmoid function which

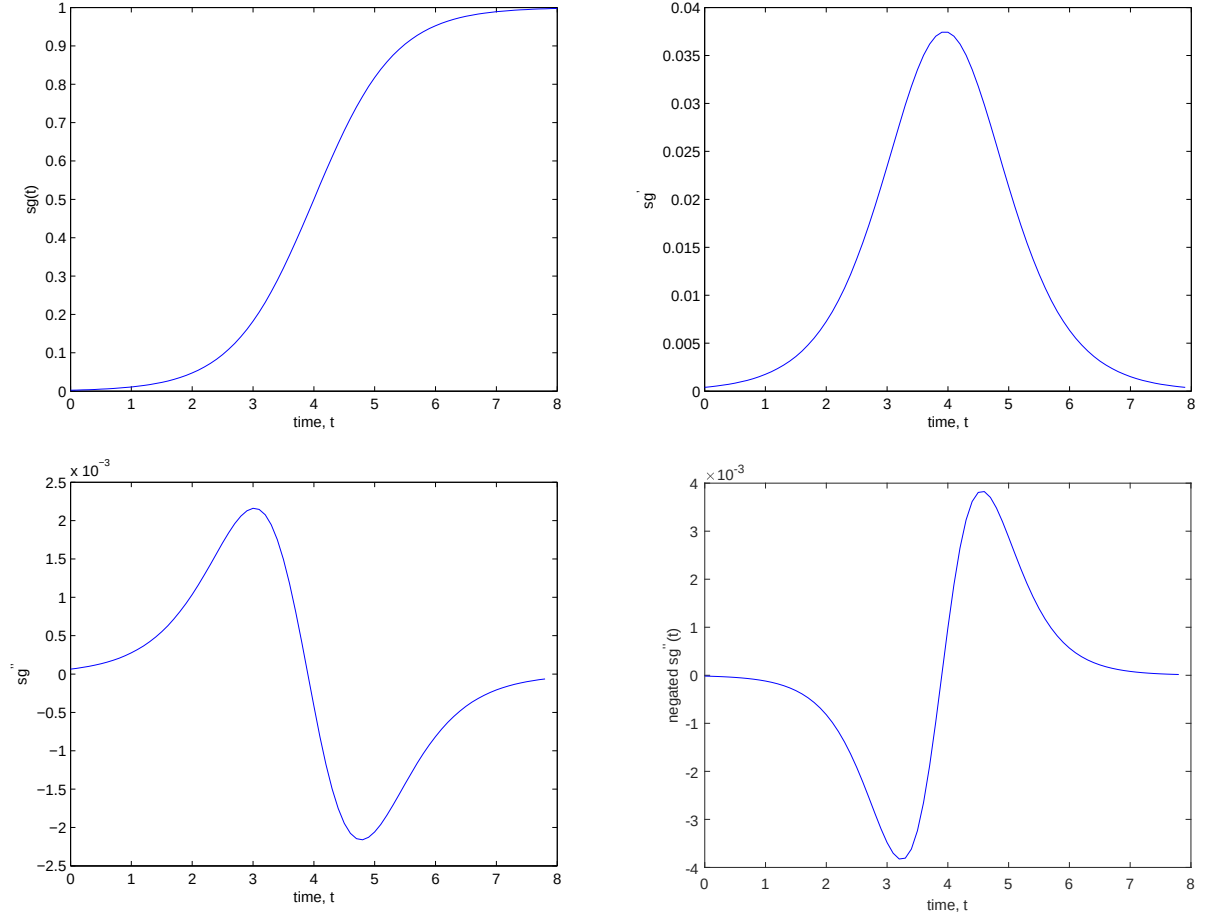


Fig. 6.15. Sigmoid function and its derivatives (top-left) logistic sigmoid function (top-right) - first derivative (bottom-left)- second derivative, and (bottom right) - negated second derivative.

is a Gaussian. Similarly the negated first derivative of the BP21 measured voltages resembles the negated first derivative of the Gaussian. This implies that the average winter difference correction function observed is almost a negated first derivative of the BP21 measured voltages.

Figure 6.18 compares the dcf averaged over 1 hr to the negated first derivative of the BP21 measured voltages also averaged over the same time. The two plots closely resemble each other throughout the whole day. The derived winter difference correction function looks like the negative of the first derivative of the BP21 measured voltages, which in essence is the second derivative of the logistic sigmoid function. So the winter dcf obtained after

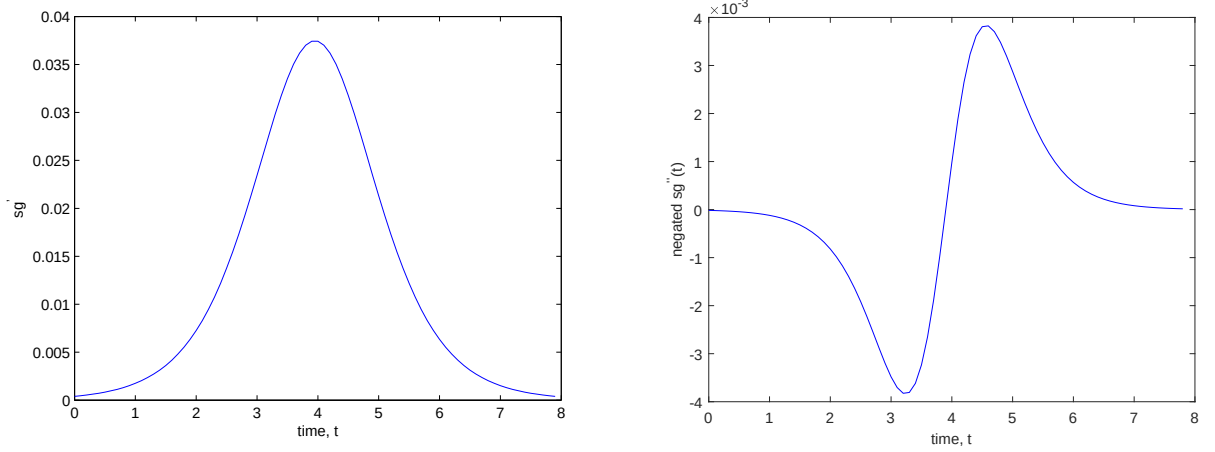


Fig. 6.16. Plot of (left) first derivative of sigmoid function, and (right) - negated first derivative of the function on left

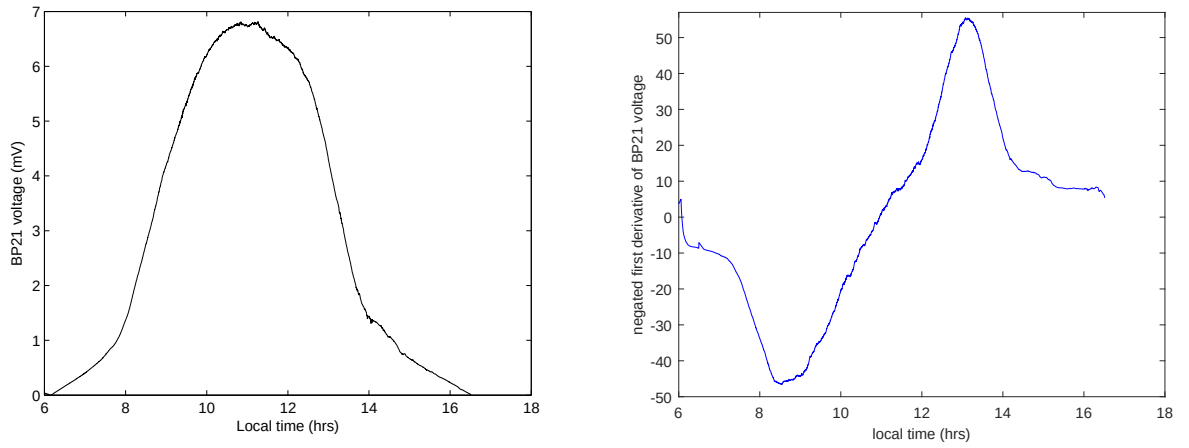


Fig. 6.17. Plot of BP21 measured voltages on a typical winter day, (left), and negated first derivative of BP21 voltages (right), both averaged over 1 hour (360 points)

negating simple differences between CMP1 measured and ANN estimated irradiances is found to be simply the negated first derivative of the BP21 voltages that are inputs to the ANN. This observation points to an interesting point that instead of using the dcf, once the daily voltages have been measured, we simply negate the first derivative of the measured voltages and add to ANN estimated irradiances to effect the required corrections for each day.

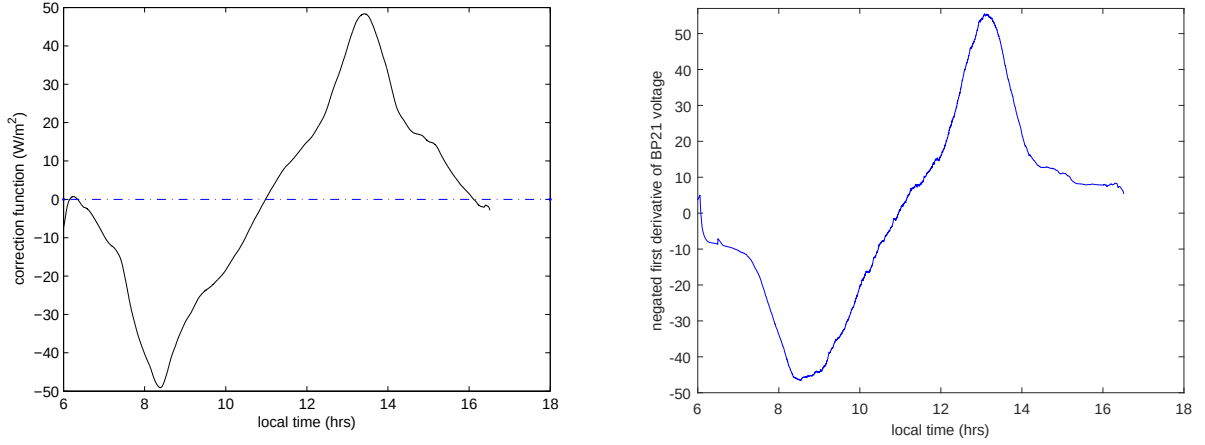


Fig. 6.18. Comparison of dcf used (left) and (right) negated first derivative of BP21 voltage for a typical winter day, both averaged over 1 hour.

6.8 Summer difference corrected irradiances

Figures 6.19 - 6.22 show summer correlations results obtained before difference corrections (row 1) and after adding the average summer difference correction function to the ANN estimated irradiances (row 3). The center figures show the dcf used. These results show much improved correlations between the corrected irradiances and CMP11 measured, for both clear and partly cloudy summer days.

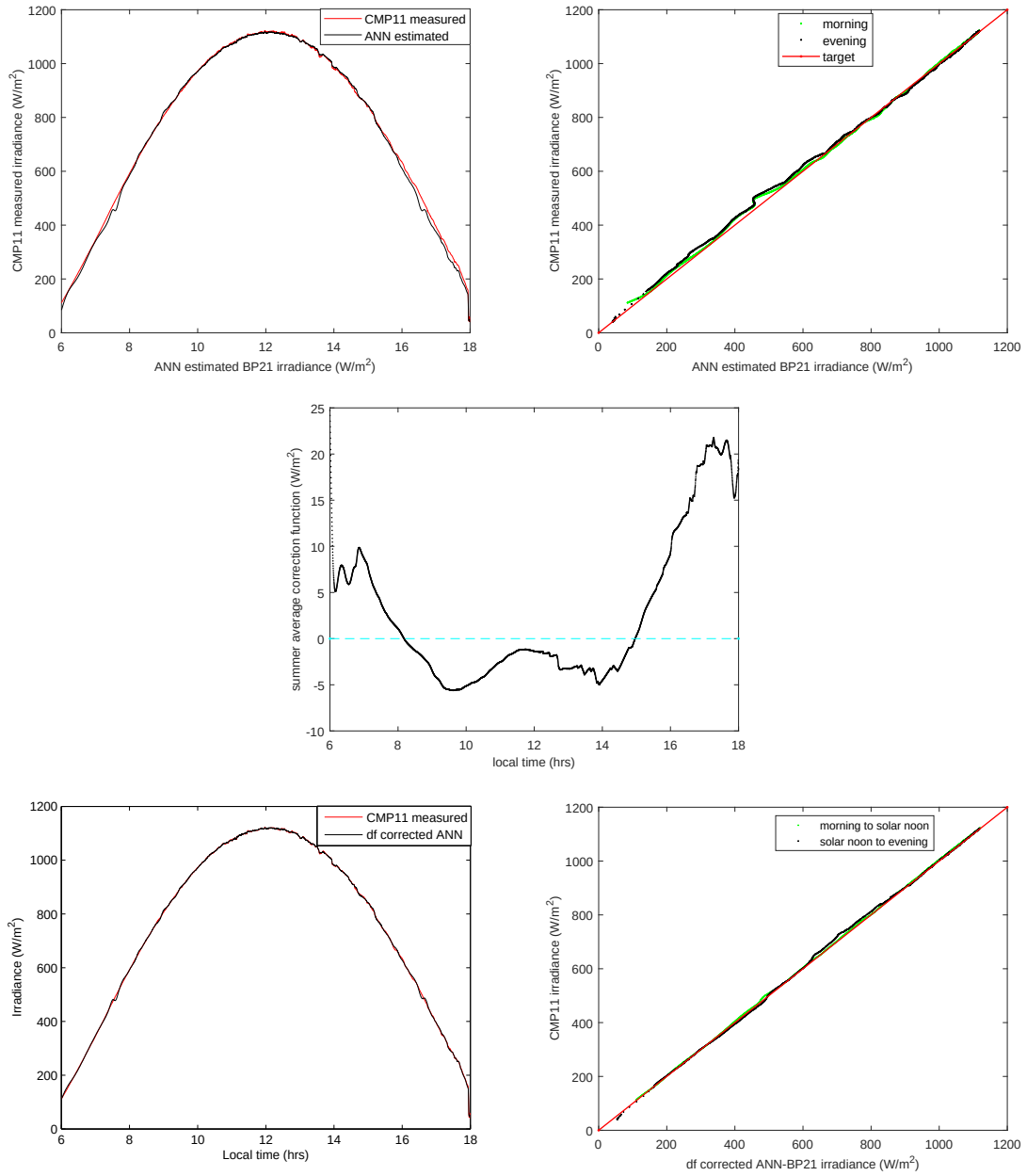


Fig. 6.19. Correlation of CMP11 and ANN estimated irradiances row 1 - before dcf, row 3 - after dcf, for 30 Nov.

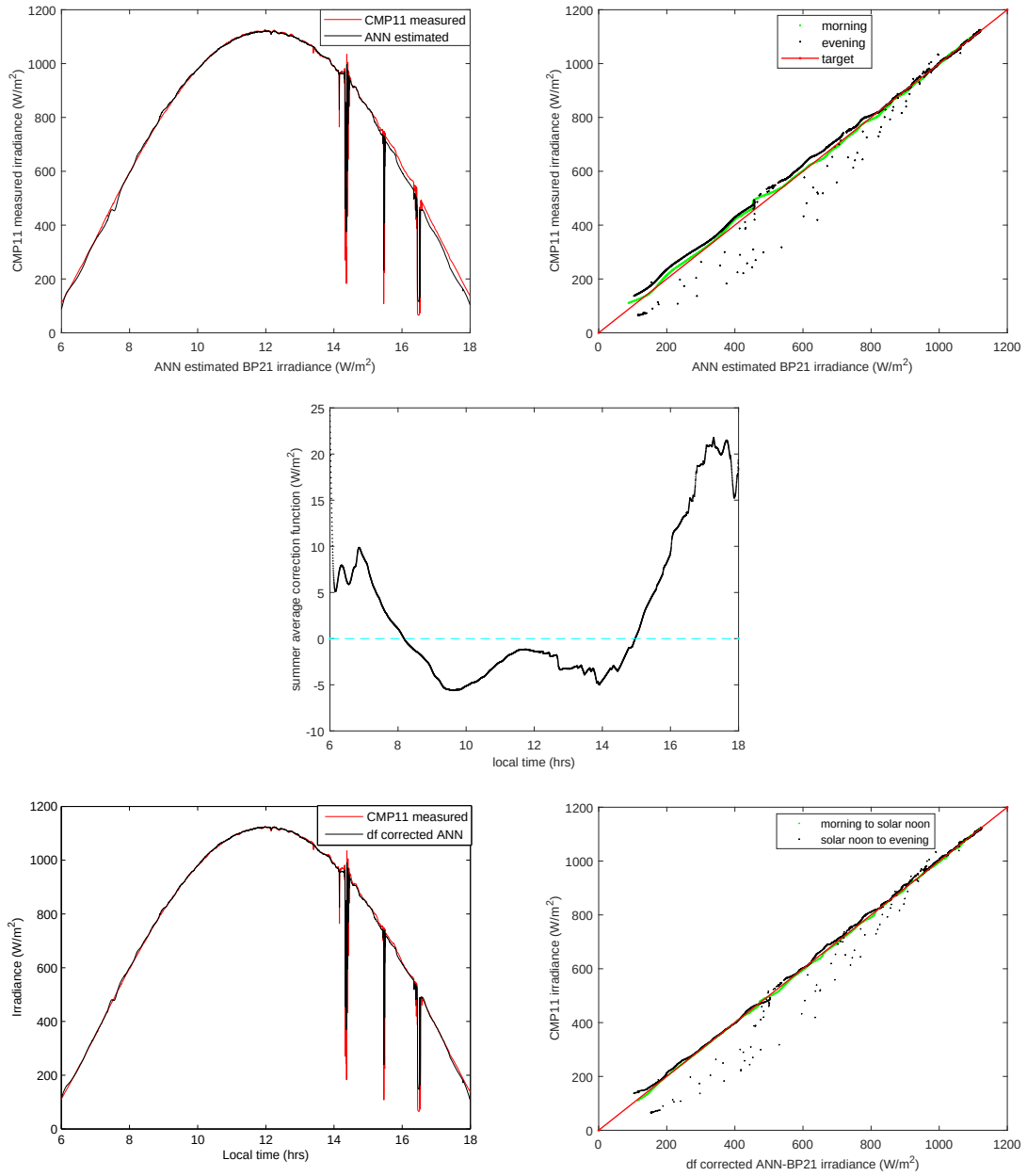


Fig. 6.20. Correlation of CMP11 and ANN estimated irradiances row 1 - before dcf, row 3 - after dcf, for 10 Oct .

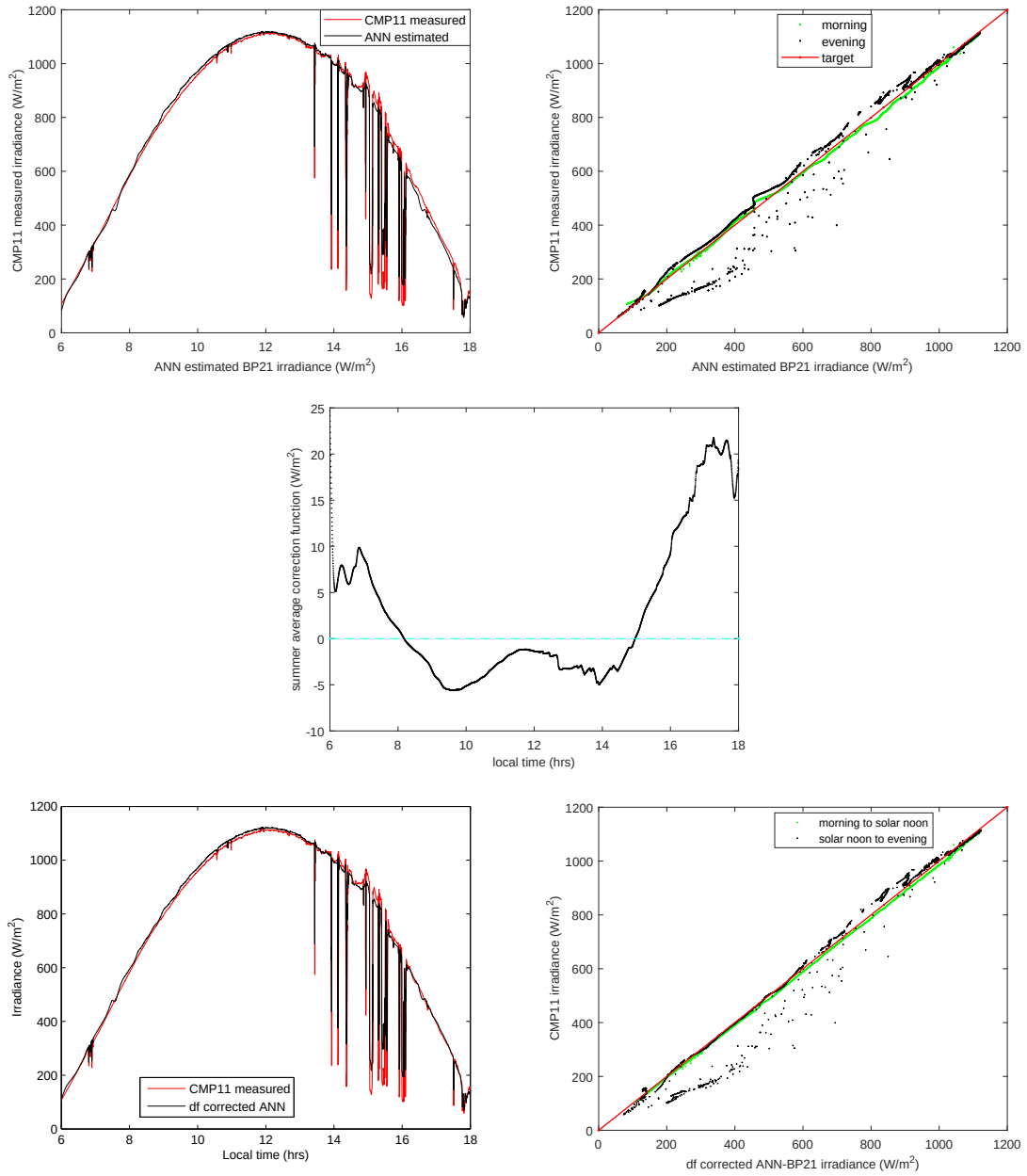


Fig. 6.21. Correlation of CMP11 and ANN estimated irradiances row 1 - before dcf, row 3 - after dcf, for 8 Sept.

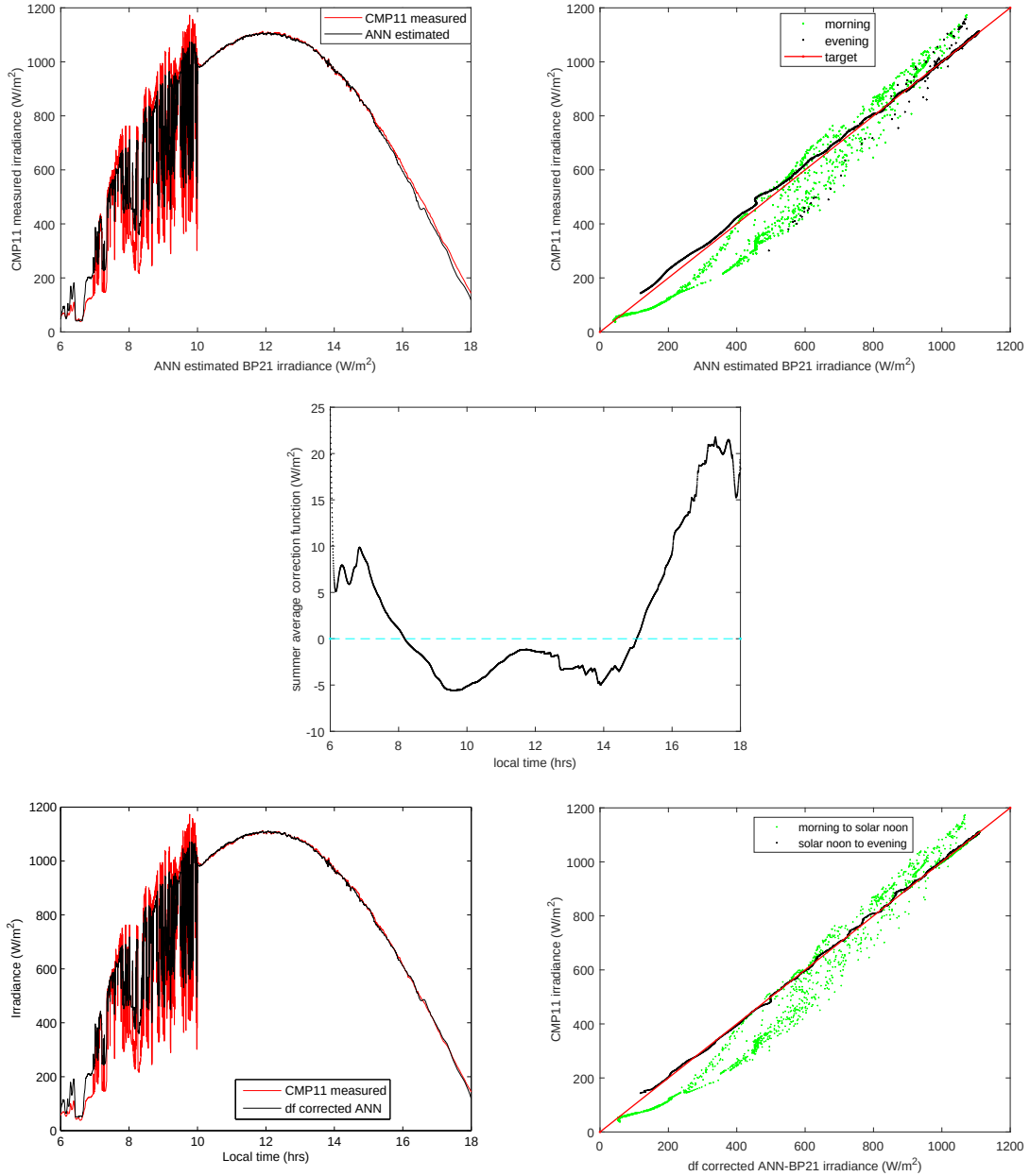


Fig. 6.22. Correlation comparison of ANN estimated irradiances row 1 - before dcf, row 2 - after dcf, for 2 Nov.

Figure 6.23 summarizes correlations between CMP11 measured and difference corrected ANN estimated irradiances for the four summer days presented, before and after difference corrections. Row 1 shows correlations for 30 Nov, row 2 is for 10 Oct, row 3 is for 8 Sept and the last row is for 2 Nov. These results show that the dcf significantly improved the correlations, even for partly cloudy days.

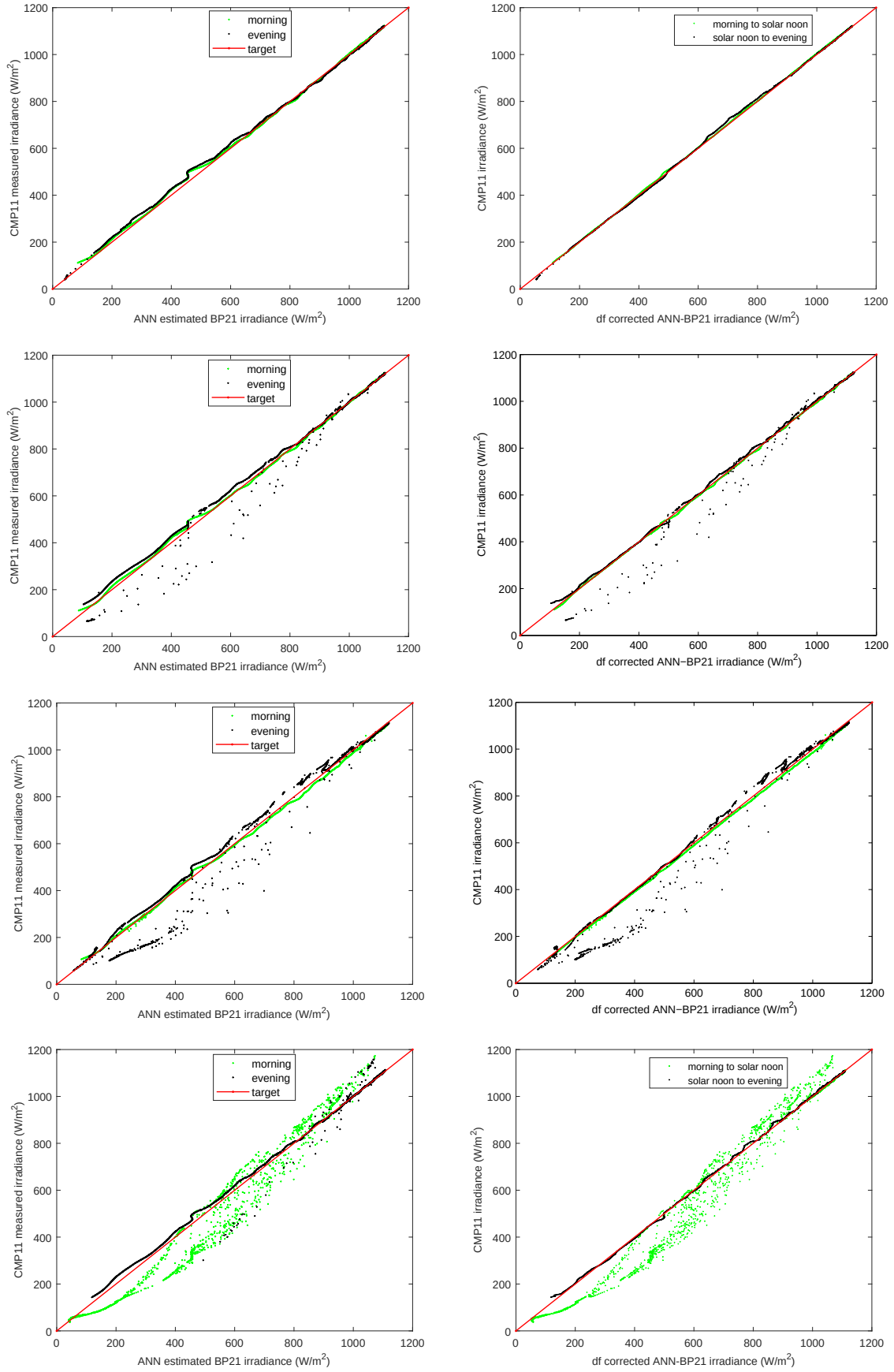


Fig. 6.23. Correlation functions for summer ANN estimated irradiances, left column - before difference corrections, right column - after.

6.9 Winter difference corrected irradiances

Figures 6.24 - 6.27 show winter correlations results obtained before difference corrections (row 1) and after adding the average winter difference correction function to the ANN estimated irradiances (row 3). The results show much improved correlations between corrected irradiances and CMP11 measured, for both clear and partly cloudy winter days. The average difference correction function used is shown in the center of each figure.

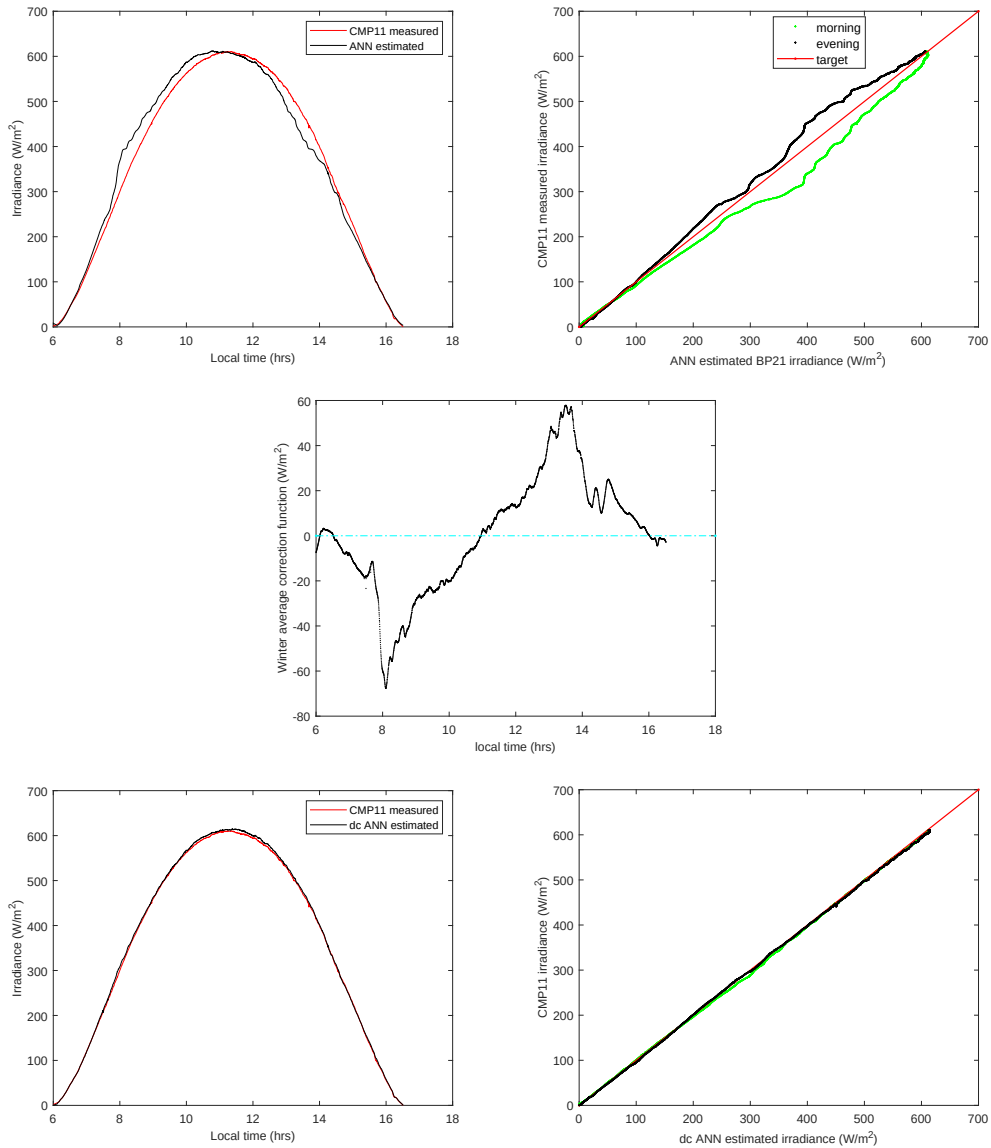


Fig. 6.24. Correlation of CMP11 and ANN estimated irradiances for 5 June, row 1- before dcf, row 3 - after dcf .

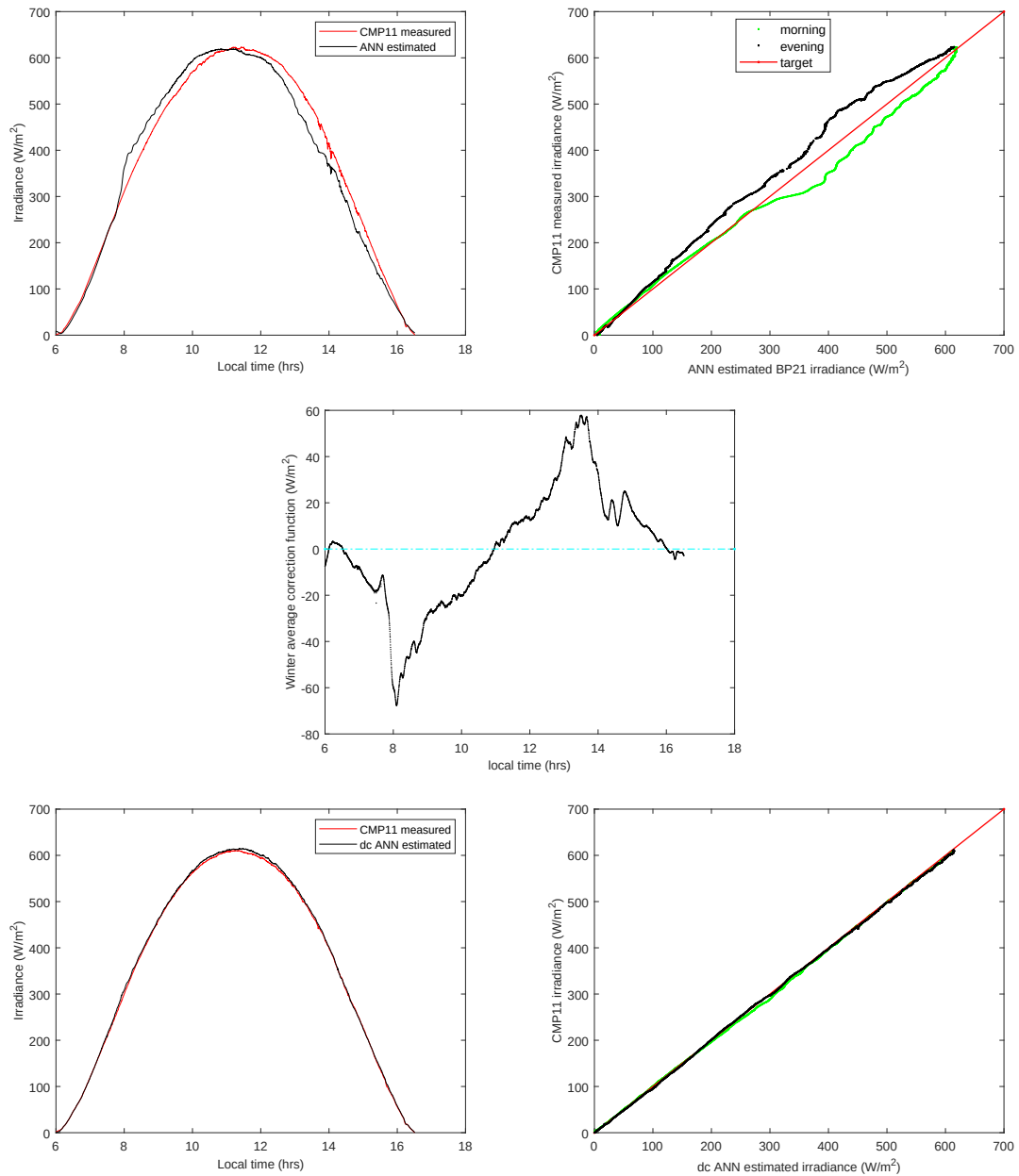


Fig. 6.25. Correlation of CMP11 and ANN estimated irradiances for 13 June, row 1- before dcf, row 3 - after dcf.

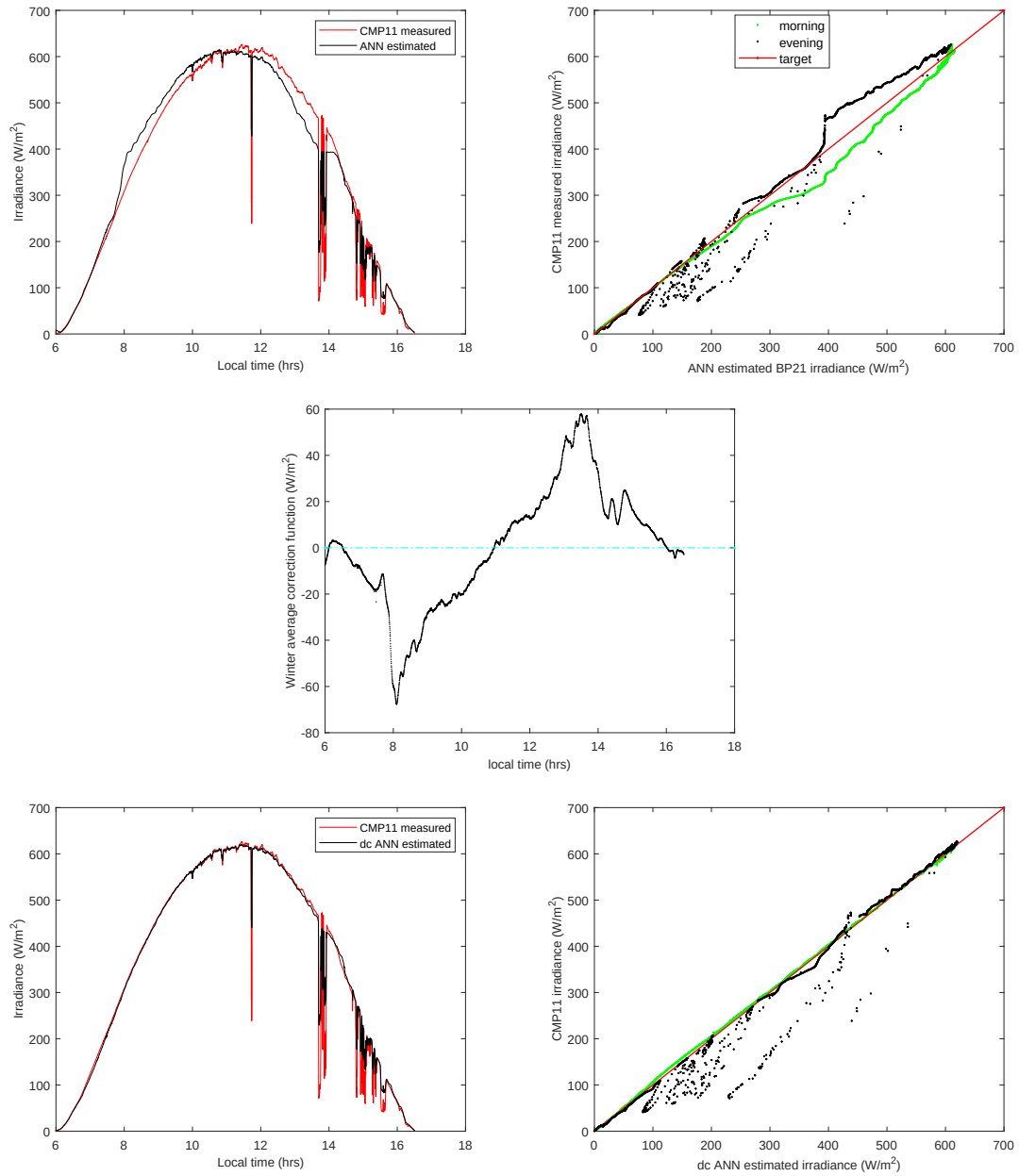


Fig. 6.26. Correlation of CMP11 and ANN estimated irradiances for 16 July, row 1- before dcf, row 3 - after dcf.

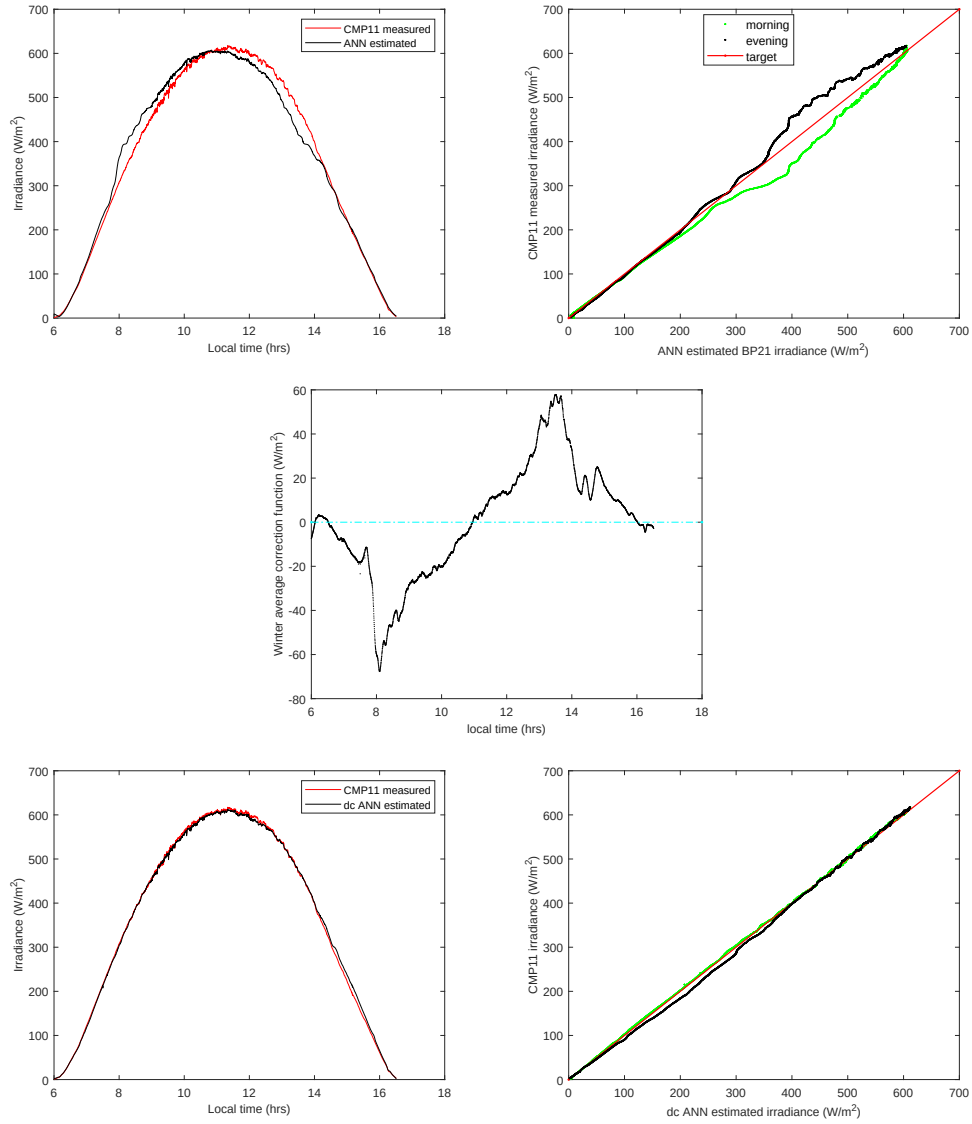


Fig. 6.27. Correlation of CMP11 and ANN estimated irradiances for 27 July, row 1- before dcf, row 3 - after dcf.

Figure 6.28 compares correlation functions for four selected winter days, before and after difference corrections were applied. Row 1 shows correlations for 5 June, row 2 is for 13 June, row 3 is for 16 July and the last row is for 27 July. Sunny days show good correlation after dc, while for partly cloudy days, e.g., panel 3, where there are fluctuations in the late afternoon, the ANN measured fluctuations appear almost exactly in the difference corrected results. The dcf significantly improved the correlations. The next section presents numerical values that show this improvement.

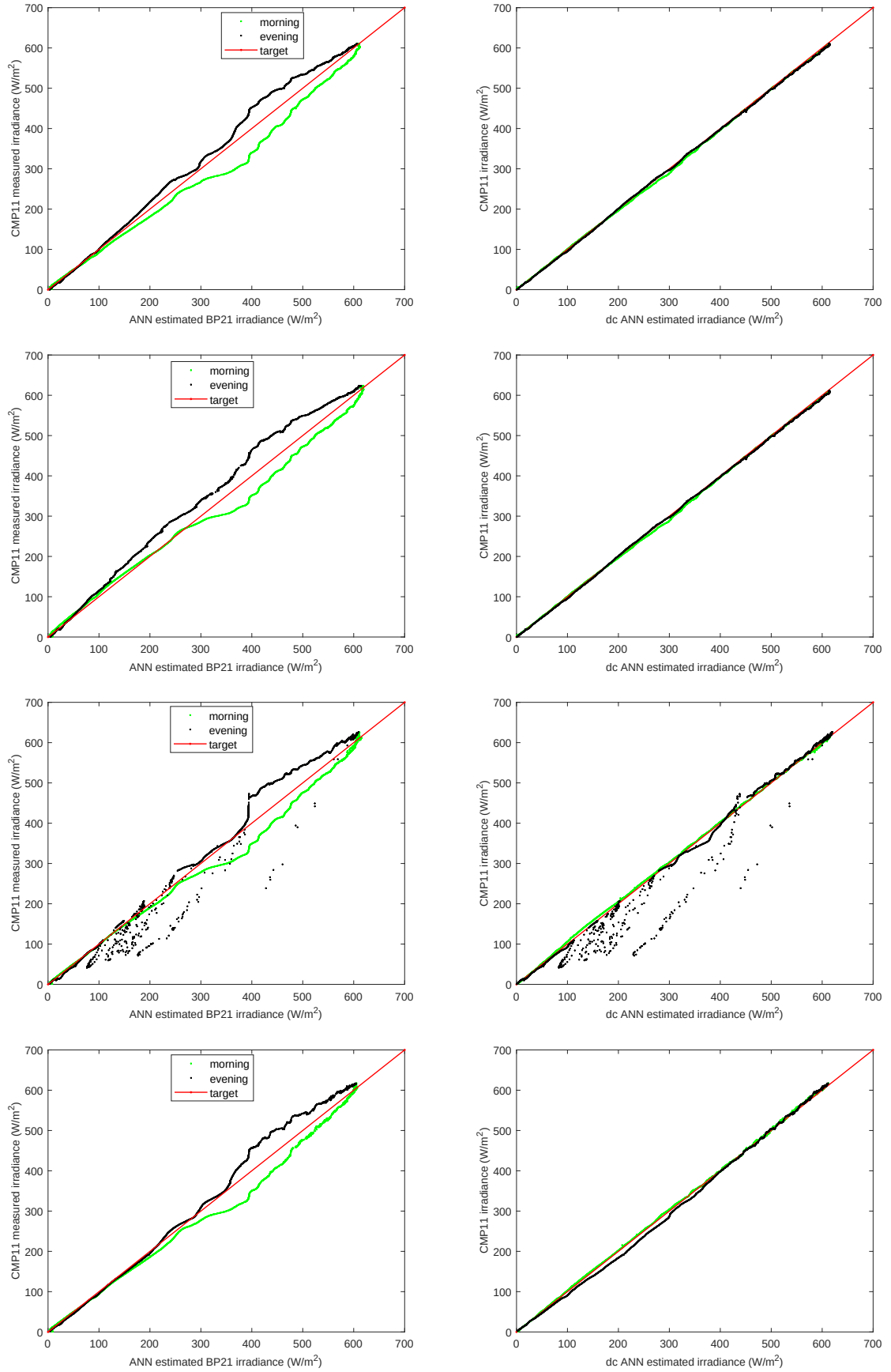


Fig. 6.28. Correlation functions for winter ANN estimated irradiances, left column - before difference correction, right column - after.

6.10 Assessment of radiometer performance

This section presents parameters that are used to rate the performance of the designed radiometer. The efficacy of the designed radiometer can be judged by comparing the ANN estimated daily irradiances with those measured by the reference CMP11 pyranometer. Both ANN estimated irradiances and ANN estimated difference function corrected irradiances were compared against the expected CMP11 measured irradiances through error analysis. Three comparison tests, namely, correlation coefficient, mean absolute error (mae) and root mean square error (rmse), were used in evaluating performance of the device. Correlation coefficient, r , was used to determine the level of association between the CMP11 measured and the ANN estimated irradiances. Both the CMP11 output (t_i) and desired output (y_i) are compared to generate errors ($t_i - y_i$) used for getting radiometer performance parameters.

The residual of an observed value is the difference between the observed value and the expected value of the quantity of interest. Residuals are defined simply as differences between CMP11 measured irradiances and ANN estimated :

$$e_i = (t_i - y_i) \quad (6.6)$$

Figure 6.29 shows plots of residuals for one typical day in each of the two seasons. It compares residuals before and after dc. Each plot is a representative of residuals for all days in each of the two seasons. Residuals before dc are simply deviations for that day, as presented earlier. Residuals before and after dc are more pronounced on partly cloudy days for both summer and winter periods as shown in row 3 of Fig. 6.29, with values going up to -200 W/m^2 . For summer there are no significant differences in the residuals before and after dc. There are significant reductions in the residuals after dc was applied to

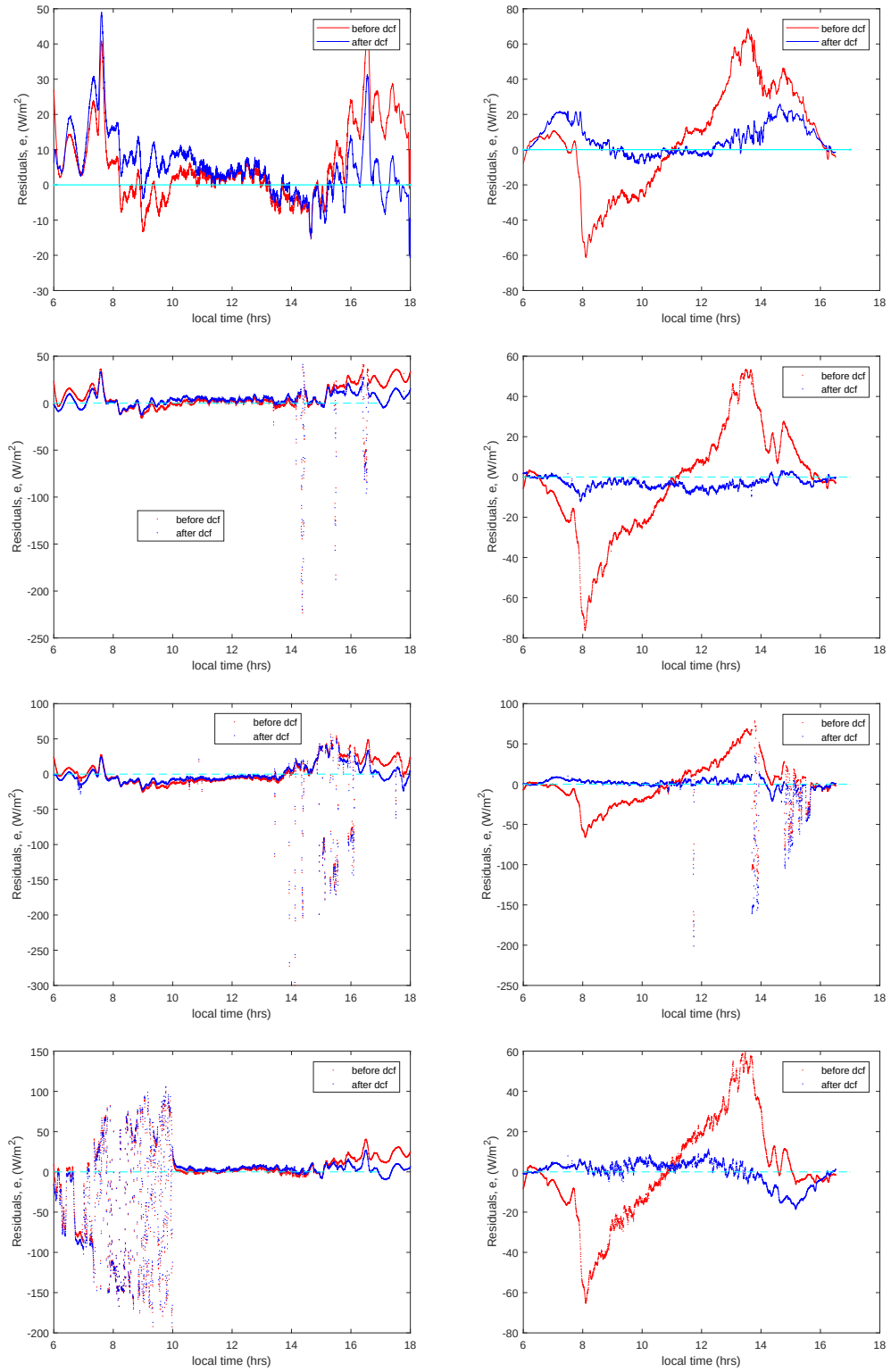


Fig. 6.29. Typical daily residuals for selected days before and after dcf, left column - summer days, right column - winter days.

ANN estimated winter irradiances, with peak values of only up to $+20 \text{ W/m}^2$ compared to $\pm 70 \text{ W/m}^2$ before dc.

The mean absolute error (mae) is another quantity which is used to measure how close the estimated values are with measured values. It is defined as the average value of the residuals.

$$mae = \frac{1}{N} \sum_{i=1}^N |t_i - y_i| \quad (6.7)$$

During summer, $N = 4321$ data points were used in the calculation of the radiometer performance parameters for that day, while $N = 3786$ were used for winter. The root-mean-square deviation or root-mean-square error (rmse) is a frequently used measure of the differences between the reference measured irradiances (true values) and the photodiode measured values (estimated). The smaller the rmse value, the better the performance of the radiometer [59]. rmse also describes the average magnitude of the errors and is defined as :

$$rmse = \left(\frac{1}{N} \sum_{i=1}^N (t_i - y_i)^2 \right)^{\frac{1}{2}} \quad (6.8)$$

The root-mean-square-error is also known as the standard deviation of the residuals.

Correlation coefficient is a measure that shows how well this radiometer output matches the desired output and is defined as [43] :

$$r = \left(1 - \frac{\sum_{i=1}^N (t_i - y_i)^2}{\sum_{i=1}^N (t_i)^2} \right)^{\frac{1}{2}} \quad (6.9)$$

This parameter may be defined either as a ratio or a percentage. Since the definition given in Eqn. (6.9) uses the ratio form, its values range from zero to one. Correlation coefficient indicates a perfect positive linear correlation between t and y if $r = 1$, perfect linear negative correlation if $r = -1$ and no correlation between network and desired output should $r = 0$. The square of the correlation coefficient is known as the coefficient of determination, r^2 and is an alternative measure to tell how well the ANN estimated irradiances relate to the CMP11 measured.

Table 6.1 presents radiometer performance parameters before and after dcf was applied to summer estimated irradiances. Subscript $_b$ stands for before while $_a$ is for after dcf. Radiometer performance is presented in terms of mean absolute error (mae), root mean square error (rmse) and linear correlation coefficient (r) between the measured target and estimated artificial neural network output, before and after difference correction. The rmse values before dc was applied ranged from 10 W/m^2 to about 22 W/m^2 . The dcf reduced the rmse by about 50%. High rmse values above 15 W/m^2 are attributed to partly cloudy weather conditions on those days. Average rmse for summer period was about $\pm 16 \text{ W/m}^2$ before the ANN estimated irradiances dcf was applied. After the difference correction, average rmse dropped to around $\pm 9 \text{ W/m}^2$.

Table 6.1: Radiometer performance parameters in summer before and after difference correction of ANN estimated irradiances.

Day	$rmse_b \text{ (W/m}^2\text{)}$	$rmse_a \text{ (W/m}^2\text{)}$	r_b	r_a	$mae_b \text{ (W/m}^2\text{)}$	$mae_a \text{ (W/m}^2\text{)}$
30 Nov	12.1	7.4	0.9996	0.9998	5.7	3.1
26 Nov	13.9	8.7	0.9984	0.9988	5.6	7.3
14 Nov	15.2	9.0	0.9975	0.9983	3.5	2.5
2 Nov	20.7	8.5	0.9915	0.9925	7.3	9.9
22 Oct	12.7	7.1	0.9933	0.9981	6.6	3.4
10 Oct	19.1	12.0	0.9985	0.9988	5.1	2.5
29 Sept	15.8	10.6	0.9944	0.9991	8.5	6.9
8 Sept	18.8	11.9	0.9959	0.9964	3.6	9.1

Table 6.2 shows radiometer performance parameters for winter period, for both before and after dc. For this period, both correlation coefficients and the mae radiometric parameters are almost the same before and after dcf. The average $rmse$ for winter period was about $\pm 27 \text{ W/m}^2$ before the ANN estimated irradiances were difference corrected. After the difference correction, the average $rmse$ obtained from all winter days used dropped significantly to around $\pm 5 \text{ W/m}^2$. mae for both seasons is almost the same before and

after dcf, averaging about 6 W/m^2 in summer and 5 W/m^2 in winter.

Table 6.2: Radiometer performance parameters in winter before and after difference correction of ANN estimated irradiances.

Day	$rmse_b$ (W/m^2)	$rmse_a$ (W/m^2)	r_b	r_a	mae_b (W/m^2)	mae_a (W/m^2)
5 June	26.47	4.02	0.9916	0.9999	2.6	3.0
13 June	29.28	10.41	0.9907	0.9994	6.5	6.0
23 June	27.35	9.88	0.9922	0.9997	8.9	8.5
30 June	27.36	5.54	0.9915	0.9999	5.4	4.9
2 July	27.05	11.19	0.9918	0.9993	6.8	7.2
16 July	27.32	3.70	0.9911	0.9999	1.2	1.6
17 July	27.42	9.64	0.9915	0.9996	7.0	7.5
27 July	25.03	5.91	0.9925	0.9997	0.2	0.2

Figure 6.30 shows a histogram of winter solar irradiance rmse before and after difference correction. There are significant improvements in rmse after difference correction as shown, from the red to the blue bars.

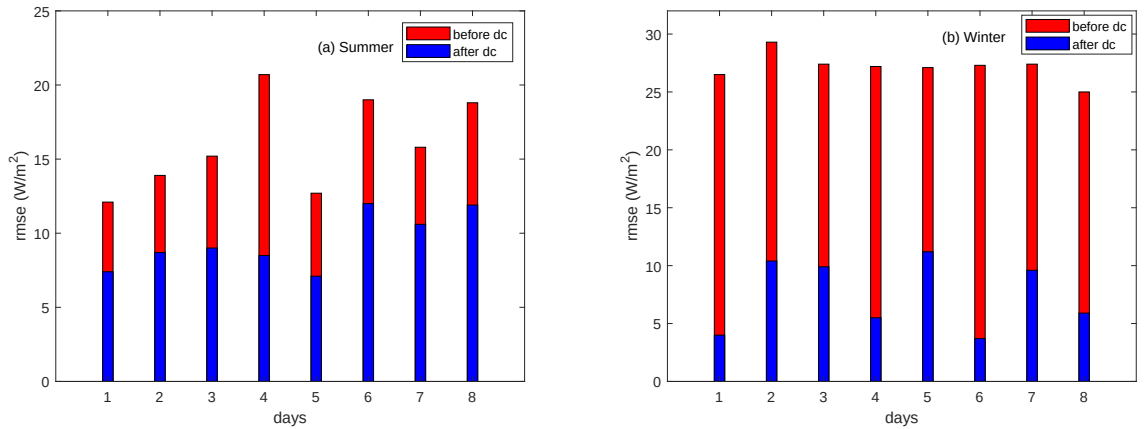


Fig. 6.30. Histogram of rmse before (red) and after difference correction (blue) : left column - summer days, right column - winter days.

Chapter 7: Conclusion and recommendations

7.1 Conclusion

7.1.1 General conclusion

A Si-photodiode radiometer was constructed and connected to a data logger for solar radiation measurements over a 6-month period. Peak irradiances were about 600 W/m^2 for winter and 1000 W/m^2 for summer. The measured photodiode voltages were used to develop ANNs. First, selected data were used to train the networks. Then different data were used to test and validate the ANNs. It was then found that using the entire data set resulted in an inaccurate single ANN model. It was then decided to split the data into two sets and develop separate models for winter and summer separately. Data from selected days were used to validate the models. In summer, the difference between ANN estimated irradiances and CMP11 measured ranged from -20 W/m^2 to $+5 \text{ W/m}^2$. After difference correction, rmse values for summer dropped from $\pm 16 \text{ W/m}^2$ to $\pm 9 \text{ W/m}^2$. In winter, ANN estimated BP21 irradiances differed by up to $\pm 60 \text{ W/m}^2$ with rmse of $\pm 27 \text{ W/m}^2$ that dropped significantly to $\pm 5 \text{ W/m}^2$ after dc were effected. A significant improvement for winter irradiance was observed after using the difference correction function. The difference correction function developed for winter ended up being the negated second derivative of the logistic sigmoid function. So any ANN estimated daily winter data has

this difference function added to correct for the non-linearities that exist. It was suggested that the differences in the difference correction function summer and winter may have been due to tilt effects.

Despite the spectral mismatches between the photodiode and the thermopile based CMP11 reference pyranometer, we have successfully used artificial neural networks to match the two instruments, and to auto correct the BP21 measured data once the measured signals have been recorded. It is believed that this design will be a good replacement of the reference CMP11 in applications that require long term measurements. In addition, there is no need to know the photodiode tilt angle prior to taking the measurements. The design can be used for prolonged outdoor irradiance measurements. At the end of the data collection period, the BP21 measured voltages are downloaded and partitioned into daily measurements starting from 06:00 hrs to 18:00 hrs for summer time. The daily measured data is then input into the saved ANN model to compute the daily irradiances corresponding to the measured voltages.

The design features and characterization of a photodiode solar radiometer have been presented. Several parameters have been used to evaluate overall performance of this automated solar radiometer. The instrument has been shown to perform fairly well at low zenith angles. The method used here performs well for clear, sunny skies and not so well for partly cloudy days where there are huge fluctuations in the measured signals. Results show differences of less than 0.5% between difference corrected ANN estimated irradiances and CMP11 measured irradiances, which is good enough for most of our running projects.

Based on this study, the following general conclusions are drawn :

- The accuracy demonstrated by the designed radiometer is adequate for many uses,

such as general purpose solar resource assessment.

- Inaccuracies inherent in the use of an uncompensated silicon detector render the instantaneous readings of the radiometer less accurate than is normally required for precise monitoring tasks such as those needed for performance assessment of concentrating solar collectors. However, post-collection correction algorithms improved the accuracy of the data and increase the instrument's suitability for these tasks.

Within the limitations of this study, the following drawbacks of the designed radiometer were made :

- The radiometer cannot return irradiances at the instant measurements are made, but after the entire day's measurements have been collected.
- The developed ANN models depend on season and are applicable only for the measurement test site of Mafikeng, however other networks for specific areas can be developed the same way.

7.1.2 Novelty

Primary and secondary commercial reference pyranometers used for solar radiation studies are beyond the reach of many laboratories in the developing world. This has led several researchers to develop empirical models for this purpose. Vast applications that use second hand data to predict global solar radiation using ANNs are widely available in literature. Unlike these, a low cost radiometer was designed and used to gather first hand data in this reported work. The instrument is portable, easy to use, and does not require accurate horizontal leveling settings. The electronic components used are low cost and readily available in many undergraduate laboratories. Undergraduate and high school students

can easily use this device to make basic measurements of global horizontal solar radiation. The use of this radiometer is foreseen to promote and stimulate research in solar energy as a green and renewable energy source. The ANN software and difference correction MATLAB scripts will be made available to undergraduate students to encourage them to do more work on renewable energy. This instrument and accompanying software may be valuable for solar radiation related experiments where resources are limited.

Despite the observed Si-photodiode's limited solar spectral response, acute field of view, and most importantly a non-linear response, it was possible to apply difference corrections to ANN estimated irradiances to match the expected irradiances. Novel corrections were suggested to improve the results to enable the photodiode design to be used to accurately measure global solar radiation incident on a horizontal surface. Average difference correction functions were proposed that were separately applied to any summer and winter ANN estimated irradiances. The difference function for winter resembled a negated second derivative of the logistic sigmoid function. When the correction was applied to the previously estimated ANN irradiances, the results obtained were very close to the expected. The method can correct for any radiometer with spectral mismatch. The method is applicable to any photodiode with different spectral responses and also tilt. The novelty of the instrument and correction method designed is that one can use any photodiode even if the spectral response does not match the reference.

Future work is to test cheap photodiode based radiometers so as to correct their response using the proposed method. This method can be used even on tilted surfaces especially for cheap radiometers used as teaching tools. Finally, literature is widely available with reported work on the application of ANN to predict solar irradiances. Some applications use sunshine hours, ambient temperature, humidity and other meteorological variables to

do this. This is probably the first time that ANN estimated results have been corrected to improve the accuracy of the estimations.

7.1.3 Recommendations for future work

Future directions aimed at further improving the designed solar radiometer include the following :

- Looking at long term performance of this design as applied to currently running renewable energy projects on the Mafikeng campus.
- Adding an offset voltage monitoring/correction option to the DAS to correct for the very small offset voltages that may be present at the output of the photodiode/opamp detector combination.
- -Si-photodiodes responsivities vary with temperature near the short and long wavelength limits of the spectral detection range. Some form of compensation may be introduced to ensure uniform responsivity of the detectors.
- The objective was to design a radiometer for global solar radiation, but because of the limited field of view of the photodiodes used, the design would perform better if it would be used for direct solar radiation measurements. However, for that to happen there is need to mount the design on a sun tracking system.
- Different photodiodes may also need to be tested to further validate the method.

It is the author's intention to consider taking this work further as part of PhD studies. Future work that is expected to form part of the PhD studies will look at explaining the following observations made from this study, that is :

- Although the possibility of tilt has been suggested, a thorough investigation will be

carried out to explain the observed different correction functions for winter and summer periods.

- Explaining why the difference correction function for winter time is related to the second derivative of the sigmoid function.
- The photodiode design could also be mounted on a vertically rotating plane to check its cosine response for both summer and winter periods.
- Temperature sensitivity is another important measure in the evaluation of radiometers. However, this study could not be done as it is not directly determined by traditional methods of radiometer performance evaluation, but rather requires specialized equipment.
- It will also be interesting to test the radiometer at another site so as to develop a new non-site-specific ANNs once a more larger measurement data set has been collected.
- Only the logistic sigmoid function was used here as the activation function. A most suitable ANN activation function may also be determined that may be used to predict irradiances with maximum accuracy.
- ANN estimated irradiances corrected using difference correction functions could also be compared against corrections based on the negated first derivative of the measured BP21 voltages.

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APPENDICES

Appendix A : Typical data file recorded on 17 November 2017

Name: Data Instr INSTR 11/17/2017 11:41:21

Owner: O. Tlhapane

Comments: Solar Irradiances

Acquisition Date: 11/17/2017 11:41:22 AM

Instrument: 34970A Address: Modules: Slot1: 34901A

Total Channels: 2

Channel Name Function Resolution Scale Gain Offset Label Test Low High HWAlarm

118 DC Voltage 5.5 TRUE 1 0 VDC Off 0 1 Alarm 1

120 DC Voltage 5.5 TRUE 106610 0 WAT Off 0 1 Alarm 1

Scan	Date & Time	118 (BP21)	120 (CMP11)	Time(s)	Time(hrs)
5979	11/17/2017 04:17:42:564	0.016437751	0.07761208	0	0
5980	11/17/2017 04:17:52:564	0.016878438	0.06652464	10	0.002777778
5981	11/17/2017 04:18:02:564	0.017323806	0.19968053	20	0.005555556
5982	11/17/2017 04:18:12:564	0.017772087	0.31055493	30	0.008333333
5983	11/17/2017 04:18:22:564	0.018226717	0.29946749	40	0.011111111
5984	11/17/2017 04:18:32:564	0.018692996	0.41034189	50	0.013888889
5985	11/17/2017 04:18:42:564	0.019155114	0.44360421	60	0.016666667
5986	11/17/2017 04:18:52:564	0.019635541	0.49914802	70	0.019444444
5987	11/17/2017 04:19:02:564	0.020117323	0.62110986	80	0.022222222
5988	11/17/2017 04:19:12:564	0.020603680	0.69872194	90	0.025000000
5989	11/17/2017 04:19:22:564	0.021090559	0.70980938	100	0.027777778
5990	11/17/2017 04:19:32:564	0.021602092	0.83187783	110	0.030555556
5991	11/17/2017 04:19:42:564	0.022103954	0.80959634	120	0.033333333
5992	11/17/2017 04:19:52:564	0.022629844	0.85405271	130	0.036111111
5993	11/17/2017 04:20:02:564	0.023126918	0.90948991	140	0.038888889
5994	11/17/2017 04:20:12:564	0.023648751	0.86514015	150	0.041666667
5995	11/17/2017 04:20:22:564	0.024176098	0.87622759	160	0.044444444
5996	11/17/2017 04:20:32:564	0.024711143	0.97601455	170	0.047222222
5997	11/17/2017 04:20:42:564	0.025235475	1.0314517	180	0.050000000
5998	11/17/2017 04:20:52:564	0.025774266	1.0203643	190	0.052777778
5999	11/17/2017 04:21:02:564	0.026327206	1.1201512	200	0.055555556
6000	11/17/2017 04:21:12:564	0.026859546	1.1090638	210	0.058333333
6001	11/17/2017 04:21:22:564	0.027429030	1.1312387	220	0.061111111
6002	11/17/2017 04:21:32:564	0.027970421	1.175695	230	0.063888889
6003	11/17/2017 04:21:42:564	0.028523152	1.2089574	240	0.066666667
6004	11/17/2017 04:21:52:564	0.029090656	1.1978699	250	0.069444444
6005	11/17/2017 04:22:02:564	0.029648487	1.2643946	260	0.072222222
6006	11/17/2017 04:22:12:564	0.030229099	1.3198318	270	0.075000000
6007	11/17/2017 04:22:22:564	0.030800870	1.3530941	280	0.077777778
6008	11/17/2017 04:22:32:564	0.031355369	1.4307062	290	0.080555556
6009	11/17/2017 04:22:42:564	0.031955228	1.4196187	300	0.083333333

Appendix B : Matlab script for creating ANN inputs and targets

```
% Script to read data into MATLAB
% Created 26 June 2018

clear all; close all; clc;

% LOAD June Data
June1 = xlsread('C:\Users\27088804\Documents\OT\MScThesis\June2017\June1.xlsx');
June2 = xlsread('C:\Users\27088804\Documents\OT\MScThesis\June2017\June2.xlsx');
June3 = xlsread('C:\Users\27088804\Documents\OT\MScThesis\June2017\June3.xlsx');
June4 = xlsread('C:\Users\27088804\Documents\OT\MScThesis\June2017\June4.xlsx');
June5 = xlsread('C:\Users\27088804\Documents\OT\MScThesis\June2017\June5.xlsx');
June6 = xlsread('C:\Users\27088804\Documents\OT\MScThesis\June2017\June6.xlsx');
June7 = xlsread('C:\Users\27088804\Documents\OT\MScThesis\June2017\June7.xlsx');
June8 = xlsread('C:\Users\27088804\Documents\OT\MScThesis\June2017\June8.xlsx');
June9 = xlsread('C:\Users\27088804\Documents\OT\MScThesis\June2017\June9.xlsx');
June10 = xlsread('C:\Users\27088804\Documents\OT\MScThesis\June2017\June10.xlsx');
June12 = xlsread('C:\Users\27088804\Documents\OT\MScThesis\June2017\June12.xlsx');
June13 = xlsread('C:\Users\27088804\Documents\OT\MScThesis\June2017\June13.xlsx');
June14 = xlsread('C:\Users\27088804\Documents\OT\MScThesis\June2017\June14.xlsx');
June15 = xlsread('C:\Users\27088804\Documents\OT\MScThesis\June2017\June15.xlsx');
June16 = xlsread('C:\Users\27088804\Documents\OT\MScThesis\June2017\June16.xlsx');
June17 = xlsread('C:\Users\27088804\Documents\OT\MScThesis\June2017\June17.xlsx');
June18 = xlsread('C:\Users\27088804\Documents\OT\MScThesis\June2017\June18.xlsx');
June19 = xlsread('C:\Users\27088804\Documents\OT\MScThesis\June2017\June19.xlsx');
June20 = xlsread('C:\Users\27088804\Documents\OT\MScThesis\June2017\June20.xlsx');
June21 = xlsread('C:\Users\27088804\Documents\OT\MScThesis\June2017\June21.xlsx');
June22 = xlsread('C:\Users\27088804\Documents\OT\MScThesis\June2017\June22.xlsx');
June23 = xlsread('C:\Users\27088804\Documents\OT\MScThesis\June2017\June23.xlsx');
June24 = xlsread('C:\Users\27088804\Documents\OT\MScThesis\June2017\June24.xlsx');
June26 = xlsread('C:\Users\27088804\Documents\OT\MScThesis\June2017\June26.xlsx');
June27 = xlsread('C:\Users\27088804\Documents\OT\MScThesis\June2017\June27.xlsx');
June28 = xlsread('C:\Users\27088804\Documents\OT\MScThesis\June2017\June28.xlsx');

June = [June3', June10', June15', June16', June17', June19', June22', June23', June24, June28'];
BP21 = June(3:3,:);
CMP11 = June(4:4,:);
JuneInputData = BP21;
JuneOutputData = CMP11;

% LOAD July Data
July1 = xlsread('C:\Users\27088804\Documents\OT\MScThesis\July2017\July1.xlsx');
July2 = xlsread('C:\Users\27088804\Documents\OT\MScThesis\July2017\July2.xlsx');
July3 = xlsread('C:\Users\27088804\Documents\OT\MScThesis\July2017\July3.xlsx');
July4 = xlsread('C:\Users\27088804\Documents\OT\MScThesis\July2017\July4.xlsx');
July5 = xlsread('C:\Users\27088804\Documents\OT\MScThesis\July2017\July5.xlsx');
July6 = xlsread('C:\Users\27088804\Documents\OT\MScThesis\July2017\July6.xlsx');
July8 = xlsread('C:\Users\27088804\Documents\OT\MScThesis\July2017\July8.xlsx');
July9 = xlsread('C:\Users\27088804\Documents\OT\MScThesis\July2017\July9.xlsx');
```

```

July10 = xlsread('C:\Users\27088804\Documents\OT\MScThesis\July2017\July10.xlsx');
July12 = xlsread('C:\Users\27088804\Documents\OT\MScThesis\July2017\July12.xlsx');
July13 = xlsread('C:\Users\27088804\Documents\OT\MScThesis\July2017\July13.xlsx');
July18 = xlsread('C:\Users\27088804\Documents\OT\MScThesis\July2017\July18.xlsx');
July19 = xlsread('C:\Users\27088804\Documents\OT\MScThesis\July2017\July19.xlsx');
July20 = xlsread('C:\Users\27088804\Documents\OT\MScThesis\July2017\July20.xlsx');
July21 = xlsread('C:\Users\27088804\Documents\OT\MScThesis\July2017\July21.xlsx');
July22 = xlsread('C:\Users\27088804\Documents\OT\MScThesis\July2017\July22.xlsx');
July23 = xlsread('C:\Users\27088804\Documents\OT\MScThesis\July2017\July23.xlsx');
July24 = xlsread('C:\Users\27088804\Documents\OT\MScThesis\July2017\July24.xlsx');
July25 = xlsread('C:\Users\27088804\Documents\OT\MScThesis\July2017\July25.xlsx');
July26 = xlsread('C:\Users\27088804\Documents\OT\MScThesis\July2017\July26.xlsx');
July27 = xlsread('C:\Users\27088804\Documents\OT\MScThesis\July2017\July27.xlsx');
July28 = xlsread('C:\Users\27088804\Documents\OT\MScThesis\July2017\July28.xlsx');
July29 = xlsread('C:\Users\27088804\Documents\OT\MScThesis\July2017\July29.xlsx');
July30 = xlsread('C:\Users\27088804\Documents\OT\MScThesis\July2017\July30.xlsx');
July31 = xlsread('C:\Users\27088804\Documents\OT\MScThesis\July2017\July31.xlsx');

July = [July1', July3', July5', July6', July8', July9', July10', July12', July13', July18', July19', ...
        July20', July21', July22', July23', July24', July25', July26', July28', July29', July30', July31'];
JulyBP21 = July(3:3,:);
JulyCMP11 = July(4:4,:);
JulyInputData = JulyBP21;
JulyOutputData = JulyCMP11;

LOAD September Data
Sept1 = xlsread('C:\Users\27088804\Documents\OT\MScThesis\September2017\Sept1.xlsx');
Sept2 = xlsread('C:\Users\27088804\Documents\OT\MScThesis\September2017\Sept2.xlsx');
Sept3 = xlsread('C:\Users\27088804\Documents\OT\MScThesis\September2017\Sept3.xlsx');
Sept4 = xlsread('C:\Users\27088804\Documents\OT\MScThesis\September2017\Sept4.xlsx');
Sept5 = xlsread('C:\Users\27088804\Documents\OT\MScThesis\September2017\Sept5.xlsx');
Sept6 = xlsread('C:\Users\27088804\Documents\OT\MScThesis\September2017\Sept6.xlsx');
Sept7 = xlsread('C:\Users\27088804\Documents\OT\MScThesis\September2017\Sept7.xlsx');
Sept8 = xlsread('C:\Users\27088804\Documents\OT\MScThesis\September2017\Sept8.xlsx');
Sept9 = xlsread('C:\Users\27088804\Documents\OT\MScThesis\September2017\Sept9.xlsx');
Sept10 = xlsread('C:\Users\27088804\Documents\OT\MScThesis\September2017\Sept10.xlsx');
Sept12 = xlsread('C:\Users\27088804\Documents\OT\MScThesis\September2017\Sept12.xlsx');
Sept13 = xlsread('C:\Users\27088804\Documents\OT\MScThesis\September2017\Sept13.xlsx');
Sept14 = xlsread('C:\Users\27088804\Documents\OT\MScThesis\September2017\Sept14.xlsx');
Sept15 = xlsread('C:\Users\27088804\Documents\OT\MScThesis\September2017\Sept15.xlsx');
Sept16 = xlsread('C:\Users\27088804\Documents\OT\MScThesis\September2017\Sept16.xlsx');
Sept17 = xlsread('C:\Users\27088804\Documents\OT\MScThesis\September2017\Sept17.xlsx');
Sept18 = xlsread('C:\Users\27088804\Documents\OT\MScThesis\September2017\Sept18.xlsx');
Sept19 = xlsread('C:\Users\27088804\Documents\OT\MScThesis\September2017\Sept19.xlsx');
Sept20 = xlsread('C:\Users\27088804\Documents\OT\MScThesis\September2017\Sept20.xlsx');
Sept21 = xlsread('C:\Users\27088804\Documents\OT\MScThesis\September2017\Sept21.xlsx');
Sept22 = xlsread('C:\Users\27088804\Documents\OT\MScThesis\September2017\Sept22.xlsx');
Sept23 = xlsread('C:\Users\27088804\Documents\OT\MScThesis\September2017\Sept23.xlsx');
Sept24 = xlsread('C:\Users\27088804\Documents\OT\MScThesis\September2017\Sept24.xlsx');
Sept27 = xlsread('C:\Users\27088804\Documents\OT\MScThesis\September2017\Sept27.xlsx');

```

```

Sept28 = xlsread('C:\Users\27088804\Documents\OT\MScThesis\September2017\Sept28.xlsx');
Sept29 = xlsread('C:\Users\27088804\Documents\OT\MScThesis\September2017\Sept29.xlsx');
Sept30 = xlsread('C:\Users\27088804\Documents\OT\MScThesis\September2017\Sept30.xlsx');

Sep = [Sept1', Sept2',Sept3',Sept4', Sept5',Sept6',Sept7',Sept9',Sept10',Sept12',Sept13',Sept14',....
       Sept15',Sept16',Sept17',Sept18',Sept21',Sept23',Sept24',Sept27',Sept28',Sept30'];
SepBP21 = Sep(3:3,:);
SepCMP11 = Sep(4:4,:);
SepInputData = SepBP21;
SepOutputData = SepCMP11;

% LOAD October Data;
Oct1= xlsread('C:\Users\27088804\Documents\OT\MScThesis\October2017\Oct1.xlsx');
Oct4= xlsread('C:\Users\27088804\Documents\OT\MScThesis\October2017\Oct1.xlsx');
Oct7= xlsread('C:\Users\27088804\Documents\OT\MScThesis\October2017\Oct1.xlsx');
Oct8= xlsread('C:\Users\27088804\Documents\OT\MScThesis\October2017\Oct1.xlsx');
Oct12= xlsread('C:\Users\27088804\Documents\OT\MScThesis\October2017\Oct1.xlsx');
Oct13= xlsread('C:\Users\27088804\Documents\OT\MScThesis\October2017\Oct1.xlsx');
Oct14= xlsread('C:\Users\27088804\Documents\OT\MScThesis\October2017\Oct1.xlsx');
Oct16= xlsread('C:\Users\27088804\Documents\OT\MScThesis\October2017\Oct1.xlsx');
Oct17= xlsread('C:\Users\27088804\Documents\OT\MScThesis\October2017\Oct1.xlsx');
Oct21= xlsread('C:\Users\27088804\Documents\OT\MScThesis\October2017\Oct1.xlsx');
Oct23= xlsread('C:\Users\27088804\Documents\OT\MScThesis\October2017\Oct1.xlsx');
Oct24= xlsread('C:\Users\27088804\Documents\OT\MScThesis\October2017\Oct1.xlsx');
Oct27= xlsread('C:\Users\27088804\Documents\OT\MScThesis\October2017\Oct1.xlsx');
Oct28= xlsread('C:\Users\27088804\Documents\OT\MScThesis\October2017\Oct1.xlsx');
Oct29= xlsread('C:\Users\27088804\Documents\OT\MScThesis\October2017\Oct1.xlsx');
Oct30= xlsread('C:\Users\27088804\Documents\OT\MScThesis\October2017\Oct1.xlsx');

Otc = [Oct1', Oct4', Oct7', Oct12', Oct14', Oct16', Oct17', Oct21',Oct23',Oct24',Oct27',Oct28',....
OctBP21 = Oct(3:3,:);
OctCMP11 = Oct(4:4,:);
OctInputData = OctBP21;
OctOutputData = OctCMP11;

% load November data
Nov23 = xlsread('C:\Users\27088804\Documents\OT\MScThesis\November2017\Nov23.xlsx');
Nov24 = xlsread('C:\Users\27088804\Documents\OT\MScThesis\November2017\Nov24.xlsx');
Nov25 = xlsread('C:\Users\27088804\Documents\OT\MScThesis\November2017\Nov25.xlsx');
Nov26 = xlsread('C:\Users\27088804\Documents\OT\MScThesis\November2017\Nov26.xlsx');
Nov28 = xlsread('C:\Users\27088804\Documents\OT\MScThesis\November2017\Nov28.xlsx');
Nov29 = xlsread('C:\Users\27088804\Documents\OT\MScThesis\November2017\Nov29.xlsx');
Nov30 = xlsread('C:\Users\27088804\Documents\OT\MScThesis\November2017\Nov30.xlsx');
Nov31 = xlsread('C:\Users\27088804\Documents\OT\MScThesis\November2017\Nov31.xlsx');
Nov32 = xlsread('C:\Users\27088804\Documents\OT\MScThesis\November2017\Nov32.xlsx');
Nov33 = xlsread('C:\Users\27088804\Documents\OT\MScThesis\November2017\Nov33.xlsx');
Nov34 = xlsread('C:\Users\27088804\Documents\OT\MScThesis\November2017\Nov34.xlsx');
Nov36 = xlsread('C:\Users\27088804\Documents\OT\MScThesis\November2017\Nov36.xlsx');
Nov37 = xlsread('C:\Users\27088804\Documents\OT\MScThesis\November2017\Nov37.xlsx');
Nov38 = xlsread('C:\Users\27088804\Documents\OT\MScThesis\November2017\Nov38.xlsx');

```

```

Nov39 = xlsread('C:\Users\27088804\Documents\OT\MScThesis\November2017\Nov39.xlsx');

Nov = [ Nov26', Nov28', Nov29', Nov30'];
NovBP21 = Nov(3:3,:);
NovCMP11 = Nov(4:4,:);
NovInputData = NovBP21;
NovOutputData = NovCMP11;

S = 9.38*exp(-6); % CMP11 sensitivity

% Winter and Summer data selected for generating the network
WinterInputData = [JuneInputData, JulyInputData];
WinterOutputData = [JuneOutputData, JulyOutputData] /S; % Convert CMP11 voltages to W/m2

SummerInputData = [SeptInputData, OctInputData, NovInputData];
SummerOutputData = [SeptIOOutputData, OctOutputData, NovOutputData]/S; % Convert CMP11 voltages to W/m2

% Winter and Summer data selected for Testing and Validating network
WinterData = [June5',June13',June23',June30, July2', July16',July17, July27''];
WinterInputDataTest = WinterData(3:3,:); % ANN Input voltages
WinterOutputDataTest =WinterData(4:4,:) /S; % Convert Targets, CMP11 voltages to W/m2

SummerData = [ Sept8',Sept29', Oct10', Oct22', Nov2', Nov14', Nov26', Nov30' '];
SummerInputDataTest = SummerData(3:3,:); % ANN Input voltages
SummerOutputDataTest =SummerData(4:4,:) /S; % Convert Targets, CMP11 voltages to W/m2

```

Appendix C : Matlab script for creating ANN network

```
% Solve an Input-Output Fitting problem with a Neural Network Script generated by NFTOOL
% Created Thu Jun 21 14:17:44 CAT 2018
%
% This script assumes these variables are defined:
%
% JuneInputData - input data.
% JuneOutputData - target data.

nN = 4321;
inputs = SummerInputData; % NB : Matlab data is input as rows!
targets = SummerOutputData;

% Create a Fitting Network
hiddenLayerSize = 10;
net = fitnet(hiddenLayerSize);

% Setup Division of Data for Training, Validation, Testing
net.divideParam.trainRatio = 70/100;
net.divideParam.valRatio = 15/100;
net.divideParam.testRatio = 15/100;

% Train the Network with odd indices
[net,tr] = train(net,inputs,targets);

% Test the Network with even indices
TestData = D28'; % Load data to be tested
Outputs = net(TestData(1:1,:)); % Row1 is BP21 measured voltage
CMP11 = TestData(2:2,:); % Row 2 is CMP11 measured irradiances

% Validating the results 1
nTime = Time';
font = 10;
figure(1);
plot(nTime(1:nN),Outputs,'r', nTime(1:nN), cBP21,'b');
xlabel('Local time (hrs)','FontSize',font); ylabel('Irradiance (W/m^2)','FontSize',font);
h_legend=legend('ANN estimated irradiance','Corrected BP21 irradiance');

% Save the network for future use
netSummer = net;
save netSummer;

load C:\Users\27088804\Documents\OT\MScThesis\netSummer.dat ; % Call saved network for validation

% Validating the results with unseen data (testing) exposed to the network
CMP11 = TestData(2:2,:); % CMP11 measured irradiances
cBP21 = sim(net, TestData(1:1,:)); % ANN corrected BP21 irradiance readings

figure(3);
```

```
plot (nTime(1:nN),CMP11,'g',nTime(1:nN),cBP21,'k'); % Plot measured and the corrected irradiances
xlabel('Local time (hrs)','FontSize',font); ylabel('Irradiance (W/m^2)','FontSize',font);
h_legend=legend('CMP11 measured','Corrected BP21');
```

Appendix D : Matlab script for predicting ANN irradiances using save ANN network

```
% Developed by O. Tlhapane - MATLAB script for predicting ANN irradiances1
%

load netSummer; % Load the saved network

Data = xlsread('C:\Users\27088804\Documents\OT\MScThesis\November2017\Nov23.xlsx'); % Load data to be tested
TestData = Data';

N = length(TestData(1:1,:)) % get number of elements in the test data

BP21 = TestData(3:3,:); % Test data is in 3rd row

CMP11 = TestData(6:6,:) ; % CMP11 measured irradiances in row 6 - AUG

ANNBP21 = netSummer(BP21); % Call the loaded network and predict with ANN

time= xlsread('C:\Users\27088804\Documents\OT\MScThesis\Time66.xlsx');
nTime = time';
nTime = nTime(3:3,:);
fc = 1;
font = 10;

figure(1); % Irradiances & BP21 voltage
[hAx,hLine1,hLine2] = plotyy(nTime,CMP11, nTime,BP21);
set(hLine1,'color','red');
hold on;
plot(nTime,ANNBP21*fc,'k');
set(hAx,'color','red'); % plot the expected correlation
set(hLine2,'color','blue');
axis(hAx(1),[6 18 0 1200]);
axis(hAx(2),[6 18 0 15.0 ]);
set(gca,'YTick',(0:200:1200),'FontSize',font);
set(hAx(1),'ycolor','k');
set(hAx(2),'ycolor','b');
h_legend=legend('CMP11 measured','ANN corrected BP21', 'BP21 measured voltage','FontSize',font-2);
xlabel('local time (hrs)');
ylabel(hAx(1),'Irradiance (W/m^2)','FontSize',font); % left y-axis
ylabel(hAx(2),'Photodiode voltage (mV)','FontSize',font); % right y-axis

hold off;

[mx id] = max(CMP11); % Get CMP11 solar noon

ms = 1.0;
figure(3); % Irradiances
plot( ANNBP21(1:id),CMP11(1:id),'xg', 'MarkerSize',ms);
ylabel('CMP11 measured irradiance (W/m^2)', 'FontSize',font);
xlabel('ANN estimated BP21 irradiance (W/m^2)', 'FontSize',font);
```

```

hold on;
plot(ANBP21(id+1:N),CMP11(id+1:N),'xk', 'MarkerSize',ms);
line([0 1200],[0 1200],'Marker','.', 'LineStyle','-', 'color','r', 'LineWidth',1.0);
hold off;

ms = 1.2;
figure(5);          % Voltages
plot(BP21(1:id),CMP11(1:id)*(9.38*exp(-6)),'*g', 'markersize',ms);
xlabel('BP21 measured voltage, (mV)');
ylabel('CMP11 measured voltage (mV)');
hold on;
plot(BP21(id+1:N),CMP11(id+1:N)*(9.38*exp(-6)),'*k', 'markersize',ms);
hold off;

```

Appendix E : Matlab script generating daily deviations for each data set

```
% Developed by O. Tlhapane - Daily deviations for each data set
%

Data = xlsread('C:\Users\27088804\Documents\OT\MScThesis\November2017\Nov29.xlsx');
cData = Data';
CMP11 = cData(4:4,:) ;           % CMP11 measured irradiances in row 6 - AUG
BP21 = cData(3:3,:) ;           % Test data is in 3rd row

n = length(CMP11);               % Length of BP21

[mx ind] = max(CMP11); % Get CMP11 solar noon

nT = nTime(1:n);

mc = -(ANNBP21(1:ind)-CMP11(1:ind)); % morning correction
ec = (CMP11(ind+1:n)-ANNBP21(ind+1:n)); % evening correction

corrS = [mc, ec];

save corrS;
```

Appendix F : Matlab script for difference correction of ANN estimated irradiances

```
% Developed by O. Tlhapane - Difference correction function -  
%  
  
Data = xlsread('C:\Users\27088804\Documents\OT\MScThesis\November2017\Nov29.xlsx');  
cData = Data';  
CMP11 = cData(4:4,:) ; % CMP11 measured irradiances in row 6 - AUG  
BP21 = cData(3:3,:) ; % Test data is in 3rd row  
  
n = length(CMP11); % get Length of CMP11  
  
[mx ind] = max(CMP11); % Get CMP11 solar noon  
  
nT = nTime(1:n);  
  
load C:\Users\27088804\Documents\OT\MScThesis\corrS; % load average correction function  
  
load C:\Users\27088804\Documents\OT\MScThesis\UNcT; % load Uncorrected ANN estimated  
  
ANNBP21 = UNcT;  
  
cTs = ANNBP21(1:n)+ corrS; % Do difference corrections  
  
save cTs; % save the df corrected data  
  
figure(30);  
plot(nTime,corrS);  
  
ms = 1.0;  
figure(1);  
plot(cT(1:n), CMP11(1:n),'xb','MarkerSize',ms);  
hold on;  
plot(CMP11,CMP11,'.r');  
hold off;  
  
font = 10;  
ms = 1.2; % marker size  
  
figure(2); % Plot CMP11 vs dfc ANN  
plot( nT,CMP11(1:n),'r', nT,cT(1:n),'k'); xlabel('Local time (hrs)'); ylabel('Irradiance (W/m^2)');  
axis([6 18 0 1200 ]);  
h_legend=legend('CMP11 measured','df corrected ANN', 'Original BP21 voltage', 'FontSize',font);  
  
figure(3); % correlation  
plot(cT(1:ind), CMP11(1:ind),'*g','MarkerSize',ms);  
xlabel('df corrected ANN-BP21 irradiance (W/m^2)');  
ylabel('CMP11 irradiance (W/m^2)');  
axis([0 1200 0 1200 ]);  
hold on;
```

```

plot(cT(ind+1:n), CMP11(ind+1:n),'*k','MarkerSize',ms);
line([0 1200],[0 1200],'Marker','.', 'LineStyle','-', 'color','r','LineWidth',1.0);
hold off;

[mx id] = max(CMP11);
figure(4); % Voltages
plot(BP21(1:id),CMP11(1:id)*(9.38*exp(-6)),'b');
xlabel('BP21 measured voltage, (mV)');
ylabel('CMP11 measured voltage (mV)');
hold on;
plot(BP21(id+1:n),CMP11(id+1:n)*(9.38*exp(-6)),'c');
hold off;

```